BRINGING PEOPLE, DATA, AND MODELS TOGETHER:

UNDERSTANDING STREAM TEMPERATURE IN THE NORTHEAST

A Master's Project Report Presented By:

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Abstract

Water temperature is one of the important characteristics of a stream that can be impacted by anthropogenic change. Such change can have significant ecological implications for the health of riparian systems. It is important for decision-makers to understand the impact of various physical characteristics on the stream temperature regime in a watershed. This research applies a statistical stream temperature model (Mohseni et al, 1998) to 905 sites across the northeastern United States to determine if such models can be useful to resource managers. Statistical analysis on the calibrated model parameters across the best-fit sites is used to provide information on watershed characteristics which may be critical to stream temperature. In addition to air temperature, which is the obvious driver of stream temperature, groundwater influence, forest coverage, urban area, and drainage area, which is representative of travel time, are the most significant watershed characteristics that impact stream temperature. While the relationships between forested and urban landscapes and stream temperature generated in this research confirm past research, a definitive relationship between groundwater and stream temperature was not established.

A predictive model of stream temperature is also developed, extending the work of Mohseni et al. (1998). This model uses watershed characteristics and meteorological data to generate stream temperatures at an ungaged location. Uses of this model include analyzing the impacts of anthropogenic changes on stream temperature regimes and the generation of realistic stream temperatures at a location for use in another model, such as the physical stream temperature model developed by Yearsley (2011). Results from the predictive model are comparable to those from the calibrated nonlinear stream temperature model analyzed.

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1. Introduction

Stream temperature is directly linked to ecosystem health, impacting physical, biological, and chemical processes (Cummins, 1974, Vannote et al, 1980). The survivability of aquatic organisms, especially cold water species, is sensitive to stream temperature regime alterations (Eliason et al, 2011 and Elliott & Elliot, 2010). Anthropogenic influence has already, and is expected to continue to change stream temperature regimes (Isaak et al, 2011, and Battin et al, 2007). An average water temperature change of just 1 or 2 ^{o}C may have severe consequences for the well-being of aquatic species. Feeding, growth, and survival rates are all dependent upon different temperature characteristics at different life-cycle stages. Stream temperature increases beyond the critical temperature for survival of a species can be lethal within minutes. Adverse effects on one species will likely produce ramifications experienced throughout the ecosystem. The monitoring and modeling of stream temperature regimes is a critical asset to decision-makers assessing ecosystem vulnerability. Monitoring and modeling promote understanding of the workings of hydrologic systems and the critical role played by stream temperature.

While air temperature is widely recognized as the primary factor influencing stream temperature, other physical attributes of a watershed have significant impacts (Mayer et al. 2012, Hebert et al. 2011, Poole et al. 2001, Bowler et al. 2012, and others). The relative impact of these factors at a given location varies depending on the physical characteristics of the watershed. Projected increases in air temperature and alteration to hydrologic systems due to climate change and other anthropogenic sources are expected to have a significant impact on stream temperature. Determining the relationships between basin properties and stream temperature improves our understanding of how stream temperature responds to these changes. Developing an understanding of which basin characteristics are correlated with resiliency of stream temperature regimes is instrumental in the management and conservation of aquatic habitats. Understanding the relationships involved in stream temperature prediction can be achieved by utilizing an existing statistical stream temperature model. This research seeks to develop a modeling framework which contributes to estimation of stream temperature at ungaged locations as well as an understanding of the factors governing stream temperature within the Northeastern United States.

This research reviews existing modeling techniques, compiles stream temperature data from various organizations within the study area, analyzes a statistical stream temperature model, and assesses the factors contributing to stream temperature regimes in New England. The collection of existing stream temperature data in the Northeast into a consistent format for analysis in stream temperature models is part of the Northeast Stream Temperature Inventory, a larger data-gathering effort that is underway in conjunction with the United States Geological Survey. The mapping of existing stream temperature logger sites will be used to plan the deployment of additional temperature loggers with the goal of achieving both coarse and fine-grain temperature monitoring. A non-linear regression model (Mohseni et al. 1998) is applied to 905 sites across the northeast. Site selection based on calibration criteria yields 195 sites suitable for further analysis. A principal component analysis (PCA) and a stepwise regression analysis are utilized to determine the watershed characteristics most significant in determining stream temperature. The PCA is also used to develop a prediction model for stream temperature at ungaged locations across the region. It is anticipated that this research will provide valuable information on the understanding of what physical characteristics contribute to robustness of thermal regimes.

2. Background

2.1. Stream Temperature Variability and Physical Characteristics of Watersheds

Variables that determine water temperature in river systems can be characterized as: drivers, insulators, and buffers. Drivers determine the flow of water and the delivery of energy to the system. Insulators affect the rate at which this heat energy enters or leaves the system. Buffers store and release energy, thus heating and cooling the system. The impact of buffering processes depends on variability within the temperature regime. If the temperature of the system remains constant, buffering processes have no impact (Poole et al, 2001). The primary factors determining stream temperature (climate, subsurface flow, vegetation, land cover, and channel morphology) can be placed in these categories. The impact of each of these processes varies both spatially and temporally in any given watershed.

2.1.1. Climatic Drivers

Meteorological conditions drive hydrologic systems and are the primary source of heat energy into the system at the stream surface. Model results from Hebert et al. (2011) support the notion that surface heat fluxes dominate over streambed fluxes. Temperature fluctuations in watersheds with long travel times (> 100 ha), are known to be governed by meteorological conditions (Subehi et al, 2009). Stream temperature is widely recognized as being strongly correlated with ambient air temperature which is used as a primary driver in many stream temperature models (Mohseni et al, 1998, Morrill et al, 2005, Ficklin et al, 2011, and Yearsley, 2011). Mohseni et al. (1998) developed a non-linear relationship between stream and air temperature that has become widely accepted as the basis for statistical modeling efforts of stream temperature.

Solar radiation also delivers heat directly into the stream system and varies depending on the solar angle and the shading of the stream surface. Shading is determined by vegetation, topography, and cloud cover. Physically-based, deterministic stream temperature models often contain solar input as a primary input (Tung et al, 2006). More recent studies indicate that solar radiation may be the most influential driver of stream temperature (Mayer et al, 2012 and Hebert et al. 2011). Mayer et al. (2012) state that net short wave radiation is more important than air temperature in the heat balance of a stream, and that both water and air temperatures depend on the heat flux from solar loading. This concept suggests the possibility that air temperature could be a secondary method of measuring flux due to solar radiation input. In larger rivers where there is increased solar input and separation from shading and subsurface sources, the variance of maximum temperature is greatest (Vannote et al, 1980). In support of the importance of both factors, a study by Subehi et al. (2009) states that larger watersheds have greater temperature variability, indicating that solar radiation and surface heat transfer dominate the water temperature determinants.

As the source of all water within the system, precipitation is another central climatic driver, entering the stream channel through both surface and groundwater flow. Groundwater flow is examined more closely in the next section. Subehi et al. (2009) found that small watersheds with steep slopes have higher stream temperature variability due to rainfall driven flows that follow air temperatures more closely. Other climatic factors such as relative humidity and wind speed can influence stream temperature. A modeling effort in New Brunswick, Canada found that evaporative heat exchange accounts for 25-31% of heat flux losses, while convective heat fluxes remain under 10% of the total for both gains and losses (Hebert et al, 2011).

In a study of 104 sites in the Pacific Northwest, Mayer et al. (2012) found that air temperature explains only 20% of the variance in regional summer stream temperatures. The addition of other variables including base flow, stream length, slope, and area of forested land in the catchment explained an additional 52% of the variance. Results of this study emphasize the importance of understanding other contributing factors to stream temperature beyond the primary climatic drivers.

2.1.2. Groundwater Sources

Groundwater influence on stream temperature regimes is another important factor in establishing stream temperature regimes. Hebert et al. (2011) found streambed flux to be approximately 20% of the total heat energy input in a watershed in eastern Canada. The groundwater component can be divided into two separate types of processes that have two distinct impacts on stream temperature regimes. Phreatic groundwater enters the system from the catchment aquifer in the basin and is a temperature driver. This type of groundwater is the source of base flow in streams in the northeast and tends to be relatively consistent in temperature, roughly the mean air temperature of the region (NGWA, 2013). Because of this feature, phreatic groundwater moderates stream temperatures throughout the year (Poole et al, 2001). The same study found these streambed fluxes to be more significant in smaller streams than larger ones. Phreatic groundwater is the easier of the two to quantify.

The second type of groundwater related to stream temperature exists as a buffering process within river systems. Hyporheic groundwater infiltrates into the alluvial aquifer from the streambed and reemerges into the streambed downstream, after having been stored for some period of time. This groundwater exchange is an important buffering process in the system, occurring across varying spatial and temporal scales. The impact of hyporheic flow depends on the variability of the temperature regime (Poole et al, 2001). A less variable system experiences a minimal effect from this type of groundwater flow.

Differentiating between types of groundwater is difficult and most studies use a single, simplified measurement of groundwater input. In a study of stream temperature dynamics in New Brunswick, Canada, Hebert et al. (2011) suggest that streambed heat fluxes serve as an energy sink during the day and an energy source at night. Mayer et al. (2012) found a negative relationship between monthly baseflow index (BFI) and August stream to air temperature ratio, suggesting that an increase in groundwater influence results in cooler summer stream temperatures. Findings from Subehi et al. (2009), show that the study site with largest difference between air and water temperatures had the greatest groundwater inflow. They also found medium-sized watersheds to be more susceptible to slope effects on groundwater infiltration. Groundwater is an influential, yet complex factor in determining stream temperature and it is important to include at least some simplified measure of subsurface flow input in temperature modeling efforts.

2.1.3. Riparian Vegetation

Riparian vegetation influences stream temperature in two ways. Vegetation shades rivers from solar radiation, reducing heat input into the system (Hebert et al, 2011 and Mayer et al, 2012). Vegetation also serves as a wind barrier directly above the stream surface. The reduction of wind reduces evaporative cooling and limits convection and advection of heat energy to and from the system (Vannote et al, 1980 and Hebert et al, 2011).

The implications of riparian vegetation on stream temperature have been widely documented. In Bowler et al. (2012), a literature review found that tree cover in riparian zones decreases mean and maximum temperatures. The magnitude of these differences however, varies. Studinski et al. (2012) found that small scale reduction in riparian canopy cover can lead to rapid increase in stream temperature, suggesting a direct correlation between canopy cover and stream temperature. The same study found that the continuity of canopy coverage matters such that small patchy disturbances have minimal impact on stream temperature. The degree of riparian shading can dictate where in the river the environment shifts from heterotrophic to autotrophic processes (Vannote et al., 1980). Although the presence of riparian vegetation is likely related to watershed land use, it is influential enough to be categorized separately in any discussion and analysis.

2.1.4. Land Use

Physical characteristics of the drainage area play an important role in stream temperature. Anthropogenic changes to the natural landscape typically result in an overall warming of the temperature regime. Urbanization, deforestation, and agricultural development are among the most common changes seen to alter stream temperature.

Mayer et al. (2012) report a negative correlation between percent forested area and August stream temperature, suggesting that increased forest area should result in lower stream temperatures. Understory coverage, which is related to forest management, has been found to increase precipitation infiltration during small rainfall events, increasing groundwater influence (Subehi et al., 2009). The same study found vegetation cover to be one of the factors most influential to temperature fluctuations in small and medium-sized watersheds.

The degree of urbanization in a watershed contributes to increased stream temperatures. Kinouchi et al. (2006) suggest that anthropogenic heat input from urban wastewater effluent is the primary cause of long-term temperature increases in the Tokyo area. In mid-size watersheds, topographic characteristics known to influence groundwater flow time and path have been found to be among the main factors in temperature fluctuations (Subehi et al., 2009). Blevins et al. (2013) propose that differences in physiological response of fish species within different temperature ranges can be used to predict the impacts of landscape alteration.

2.1.5. Channel Morphology

Channel structure, determined in part by the other processes that drive stream temperature, influences the temperature regime through exposure to temperature drivers as well as both insulating and buffering processes. Channel size, shape, width, and pattern all determine the degree of shading and insulation from riparian vegetation as well as the surface area available for heat exchange. A wider channel, for example, absorbs more solar radiation and is shaded less than a narrow channel. Hyporheic flow, the primary buffering process in most systems, is dependent on streambed topography, substrate, and channel pattern. In-stream flow rate, which determines how long water is exposed to air and solar radiation, is dictated by channel slope. Mayer et al. (2012) found variation in summer thermal regimes between sites to depend on channel slope and length. The concept behind this finding is that shorter travel time allows less time to gain heat through climatic drivers, meaning steeper slopes and shorter reach lengths produce lower temperatures overall. Greater temperature fluctuation with increased flow time, as determined by Subehi et al. (2009), supports this concept. A study of geologically distinct zones in eastern Canada showed sites with more exposed igneous bedrock, poor soil layers, and less erosion to have lower water temperatures (Neff and Jackson, 2012). The channel morphology of these sites lacks the typical pool and riffle morphology, which results in shorter travel time. While channel morphology may be difficult to model explicitly outside of reach specific models, it may be represented indirectly through geologic and topographic properties.

2.2. Ecological Implications of Stream Temperature

Stream temperature regimes are a critical component of ecosystem health, which can be defined as having the ability to maintain structure and function under external stress (Costanza & Mageau, 1999). Physiology, health, population, and distribution of aquatic organisms can all be linked to various measurements of stream temperature. A basic understanding of the River Continuum Concept (RCC) is necessary to link the well-being of these species to their surrounding habitat.

2.2.1. River Continuum Concept

Vannote et al. (1980) developed the RCC to describe the interactions between the physical attributes of a river system and the biotic communities present within it. This model suggests that a balance is maintained across the downstream gradient of changing structural conditions between lotic organisms and their surrounding environment.

Organisms are classified into four distinct groups based on their function in the river continuum, a concept extending the work of Cummins (1974) that sought to classify organisms based on function in place of traditional taxonomic definitions. Shredders, collectors, and grazers all consume organic plant matter of different types, while predators feed on other organisms. Shredders reduce coarse particulate organic matter (CPOM) to fine particulate organic matter (FPOM) and are dominant in headwater systems. Grazers are most common in mid-sized rivers, where algal growth is abundant. Further downstream, FPOM is more readily available from processes occurring upstream. FPOM availability results in a shift in the biological community to being primarily comprised of collectors. This downstream biological gradient forms the basis of the Vannote et al.'s river continuum concept which is visually represented in Figure 1.

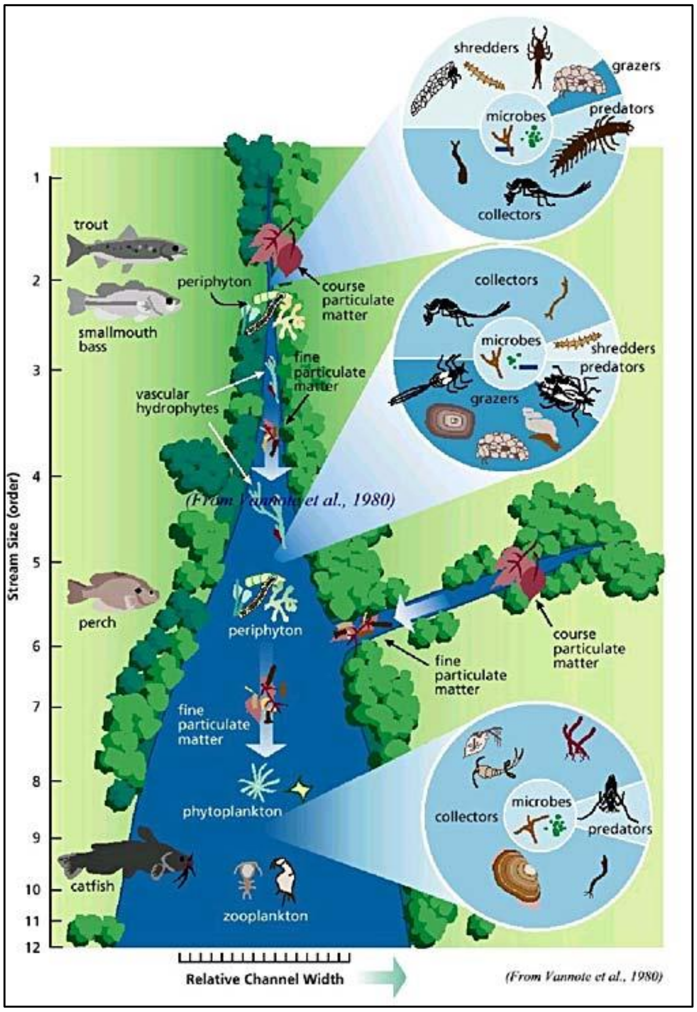

Figure 1: Relative relationships of biological communities in the River Continuum Concept as described by Vannote et al. (1980).

Vannote et al. (1980) state that community structure, along a lotic system, is arranged so that variance in system structure and function is minimized by energy efficient processing of organic material. System stability depends on how well this structure is maintained during environmental variations. In systems with large temperature fluctuations, the presence of specific biota is crucial to maintaining this stability (Vannote, 1980). Anthropogenic perturbations to the system, with varying impacts on temperature at different parts of a stream, cause the distribution of the river continuum structure to shift upstream or downstream (Vannote et al., 1980 and Poole & Berman, 2001). This effect emphasizes the importance of developing an understanding of the impact of anthropogenic changes on temperature regimes.

2.2.2. Identifying classes and assemblages through temperature regimes

As discussed in previous sections, temperature regimes vary across different sections of a river. The distribution of functional classes across the system, as described by the RCC, is at least partially temperature dependent. This relationship allows researchers to group organisms into classes and assemblages based on stream temperature.

The rate of conversion from CPOM to FPOM described in the previous section, and the flocculation of dissolved organic matter (DOM) to FPOM, are temperature dependent processes (Cummins, 1974). This dependence is due to the fact that particulate organic matter retention characteristics, the presence of material processing organisms and their metabolic rates, are influenced by temperature. The same study uses the temperature dependent ratio of heterotrophy to autotrophy in the definition of functional groups based on organic matter processing. The result is that the presence and distribution of the process oriented functional groups described by Vannote et al. (1980) may be defined by temperature regimes.

A number of studies have focused on the impact of temperature regimes on the grouping of biotic communities. Higgins et al. (2005) classifies freshwater systems based on small scale aquatic ecosystem patterns scaled within larger geographic units. Temperature is among the attributes identified as having an influence over biodiversity distribution in fresh water ecosystems. Vannote et al. (1980) state that this biodiversity is dependent on the physical stability of the system, with greater biodiversity or complexity occurring in systems with a variable physical structure. Hoehinghaus et al. (2006) found that temperature extremes with shrub and forest land use classifications explained 50% of explained taxonomic variation of 85 fish species in 6 river basins in the state of Texas. The study predicts the addition of annual temperature extremes to the habitat template used to define functional groups that comprise fish assemblages. In a study that yielded similar results, Neff and Jackson (2012) found differences in fish assemblages between sites on and off of the Canadian Shield (a large area in eastern Canada comprised of igneous rock, a thin soil layer, and atypical morphology where normal pool and riffle structure is lacking due to limited erosion). Temperature was included as a dominant abiotic variable associated with off-Shield sites, while brook trout and shiner, a fish found in pools of clear, cool streams, were strongly associated with on-Shield systems. Additionally, a small portion of the fish assemblage variance could be attributed to land use factors. Overall, temperature plays an important role in the grouping of aquatic species.

Grouping species solely by temperature however, may be muddled by intra-species variation in temperature tolerance. Eliason, et al. (2011) found variation in physiological adaptation to thermal regimes among different sockeye salmon populations within a single watershed. They conclude that the adaptation of thermal limits occurs at a local scale as different populations migrate to separate areas of the watershed. Experimental results show that creek chub inhabiting differing thermal regimes respond differently to thermal stresses (Blevins et al., 2013). Streams with forested and agricultural riparian zones were compared, with temperatures presumably warmer in agricultural watersheds. The landscape-level differences were shown through reduced responses of stress to hypoxia by the agricultural located fish, which were calculated to consume 15% less energy in response to the thermal challenge. Higgins et al. (2005) suggest the need for developing empirical relationships between stream temperature and landscape variables in classifying microhabitat. These relationships could be used in attempts to classify freshwater systems with the purpose of planning for biodiversity conservation.

2.2.3. Lethal temperatures

Riverine ecosystem vitality is often linked to the health and success of the native fish species. In the Northeast, cold water species are of particular concern. These species are an indicator of the overall state of the ecosystem in which they reside, making it necessary to understand the threshold at which stream temperatures become lethal. Temperature limits vary across different species and life stages, but general trends exist. Eliason et al. (2011) found that aerobic scope, cardiac scope, and the scope for heart rate are all positively correlated with stream temperature in various sockeye salmon populations. The scopes referred to are defined as the range from rest to maximum exertion. Thus, under higher temperature conditions, more energy is required to perform the same actions than in cooler temperatures. This also means that individuals accustomed to cooler temperatures will experience greater difficulty with temperature increases. The same study found variation of physiological adaptation to thermal regimes among sockeye salmon within a watershed. Table 1 presents the ranges at which these temperature increases become lethal to some select species in different locations (Elliott & Elliott, 2010). Incipient lethal temperatures are those the species can tolerate for up to 7 days whereas ultimate lethal temperatures refers to temperatures the fish cannot tolerate for short period of time, typically 10 minutes. It should be noted that differences between these two classifications are small and occasionally even overlap.

	Atlantic salmon (*Salmo Salar*)		brown trout (*Salmo trutta*)		Arctic charr (*Savelinus alpinus*)	
	Lower	Upper	Lower	Upper	Lower	Upper
Eggs	0	16	0	13	0	8
Alevins						
Incipient	0-2	23-24	0-1	20-22	0-0.3	19-21
Ultimate	0-1	24-25	0	22-24	0-0.2	23-27
Parr + smolt						
Incipient	0-2	22-28	0-0.7	22-25	0-1	22-23
Ultimate	-0.8	30-33	-0.8	26-30	-1	26-27
Feeding	0-7	22-28	0.4-4	19-26	0.2	21-22

Table 1: Critical temperatures (^{o}C) for survival at different life stages of Atlantic salmon, brown trout, and Arctic charr as presented by Elliott & Elliott (2010).

While it is necessary that the habitat temperature of these species remain between the temperature limits, anthropogenic changes to temperature regimes may come in forms differing from just lethal temperatures. Focusing solely on lethal temperatures may not be the most effective method for assessing the health of a species. The next section discusses other important measurements of temperature that matter to overall ecosystem health.

2.2.4. Ecologically Important Temperature Metrics

Similar to many other aspects of natural systems, the temperature impacts on organisms are complex and not fully understood. More conditions than simply mean and maximum temperature have an impact on ecosystem health. Poole and Berman (2001) suggest that anthropogenic changes may impact the spatial and temporal distribution of temperature differently and that significant changes may occur long before being detected by changes in the mean temperature. Magnitude, timing, duration, habitat type, species, population, and life stage are some of the factors that determine the effect temperature will have on a given organism.

Stream temperature variability is one of the ecologically important metrics. Vannote et al. (1980) state that system stability in large rivers should be correlated with a reduction in the variance of diel temperatures. Common temperature metrics, including seasonal and 7-day mean and maximum temperatures, were used in a study by Butryn et al. (2013) to predict brook trout proportion in a small Vermont watershed. The metrics were sufficient but failed to successfully capture temperature variation, leading the authors to develop new metrics to account for this limitation. Temperature event frequency, duration, and magnitude are among the new metrics used to capture stream temperature variation. Incorporation of the study's new metrics with the commonly used metrics improved accuracy in predicting brook trout distribution. Steel et al. (2012) supports the importance of stream temperature variability which they found to have a significant influence on the emergence timing of Chinook salmon eggs as well as the stage of development at emergence.

After hatching, the smolt life-cycle stage is the most vulnerable as migration is being initiated while the fish are still relatively small in size. McCormick et al. (1998) make the case that high temperature increases have serious implications for smolt survival in the wild, with smolt timing being affected by stream temperature. The same study suggests that spring temperature increase is particularly important in smolt run timing, which tends to occur around 10^{o}C for Atlantic salmon and brown trout. While the typical measurements of mean and maximum temperatures are critical to the survival of aquatic organisms, the implications of temperature regimes go well beyond these metrics.

Given the importance of the relationship between stream temperature and ecosystem processes, coupled climate-stream temperature predictions are essential for developing robust aquatic conservation strategies and understanding the factors most likely to influence stream temperature regimes. This research attempts to further this understanding through the application of a model developed for natural resource managers. The model will allow users to use physical characteristics of the watershed, such as the ones described in section 2.1, to predict aspects of the air to stream temperature relationship at a location. Relationships between basin characteristics and stream temperature regimes may be drawn to inform which features are most influential. This understanding can be used in conjunction with other information such as species presence to develop conservation targets.

2.3. Study Area

The study area of this research focuses on the northeast United States, including streams in Connecticut, Massachusetts, Vermont, and New Hampshire. Land cover, topography, geology, and climate vary significantly across this region, allowing for a broad, comprehensive investigation of many different factors contributing to stream temperature. The average air temperatures in the region range from roughly -10 - 0 ^{o}C in the winter and 20-25 ^{o}C in the summer. The variability of weather conditions in the region is noteworthy, and conditions can deviate largely from these averages. The region's average annual precipitation of 40-50 inches is evenly distributed throughout the year (NOAA, 2012). This region is predicted to experience climate change impacts that will impact stream temperature. Average annual air temperatures in the region are projected to increase by roughly 1 to 2 ^{o}C by 2050 (Maurer et al., 2007). A historical decrease in the snow/rain ratio (Huntington et al. 2003), as well as a historical increase in precipitation and streamflow with earlier springtime peak flows (Huntington 2009), implies hydrologic changes to the region that will alter streamflow regimes. The focus of this research is to identify basins in the study area with appropriate qualities for robust stream temperature regimes under climate change. These temperature regimes will have the least amount of deviation from the norm under changing meteorological conditions. The choice of study area is also concurrent with other research in progress within the Northeast Climate Science Center.

2.4. Modeling Stream Temperature

Assessing the effects of climate change and other anthropogenic changes on riverine systems requires accurately modeling stream temperature over large spatial scales and along varying stream orders. It is known that organism diversity varies along the river continuum (Vannote et al., 1980), as do the physiological coping mechanisms in response to changes within an ecosystem. Adaptation and physiological response to thermal regime changes among fish species are shown to be specific to local populations (Eliason et al., 2011 & Blevins et al., 2013), emphasizing the importance of monitoring and modeling stream temperature on a fine scale. This juxtaposition of modeling broadly and accurately, representing fine scale dynamics, is a challenge as models are typically designed to perform well at large scales or for a specific fine scale location, but not both.

Cost reductions in stream temperature monitoring technologies, as well as developments in geographic information systems (GIS), have improved our ability to gather data and analyze stream temperatures. The influx of easily accessible and useable data emphasizes the value of viable stream temperature models. Numerous model paradigms have developed to accurately predict stream temperature. These models vary in their complexity, spatial and temporal resolution, data requirements, and the resources required to construct and execute these models. Commonly, stream temperature models are chosen based on the data and time available for the modeling effort. When data are limited simple statistical models may be most suitable, such as linear regression between air and water temperature (Morrill et al., 2005, Neitsch et al., 2005, & Yearsley 2011).

Statistical methods are the simplest of the existing model types, with the smallest data requirements. A paired time series of air and stream temperature measurements are the only data requirements for these regression models. These models use a function of air temperature fit to the distribution of stream temperature data. Calibrated parameters are estimated to adjust the fit of the function to the measured stream temperature data.

The type of regression varies depending on the number of parameters and what they represent. Morrill et al. (2005) compares the effectiveness of linear and non-linear regression models used to predict the relationship between air and stream temperatures. In Morrill et al. (2005), the effect of changes in climate on stream temperature and dissolved oxygen levels is explored. Stream temperature data collected from 43 rivers and streams across 13 countries from Global Learning and Observations to Benefit the Environment (GLOBE) are used to calibrate the model. Predicted future air temperature changes are calculated from the United Kingdom Meteorology Office (UKMO) Hadley Center's Climate model (hadCM3). Equations are developed for each site and mean predicted air temperature for 2095-2099 is input into the models. 1, 3, and 7 day air temperature averages are tested to determine the impact on results. The non-linear regression model from Mohseni et al. (1998) is used in an attempt to represent some water bodies which tend to have temperature thresholds at higher air temperatures.

Consistent with Mohseni et al. (1998) and other previous studies, the findings of Morrill et al. (2005) suggest that most nonlinear regression models tend to have higher Nash-Sutcliffe coefficients of efficiency (NSC) and lower RMSEs than linear models. Results show a longer time period of averaged air temperature produces improved correlation, with the use of daily air temperatures having higher RMSEs than weekly temperatures. Function slope coefficients are shown to decrease with increasing elevation and slopes less than 0.6 tended to have lower NSC values. No correlation exists between drainage basin size and the relationship of air to stream temperature. The study concludes that the future dissolved oxygen levels will depend partially on the seasonal timing of water temperature increases.

The results of Morrill et al. (2005) suggest that an S-shaped function is the best choice of fit for the air to stream temperature ratio. The nonlinear model shows that as air temperature passes the inflection point and approaches the maximum stream temperature of the curve, the rate of water temperature increase declines. When the linear model performs well, the nonlinear model provides little improvement and neither method consistently predicts the highest observed temperatures. If the air to stream relationship does not taper on this upper end, the nonlinear model will perform poorly in climate change predictions. Improvement is seen when using the seasonal hysteresis method. Noting these results, along with the widespread application of the model developed by Mohseni et al. (1998), it can be concluded that among statistical models the non-linear relationship is more accurate than the linear relationship.

3. Methodology

The methodology of this research begins with stream temperature data collection from various agencies with monitoring operations in the region. An existing statistical stream temperature model, representative of the air to stream temperature relationship, is then applied to the data. The effect of hysteresis on the air to stream temperature relationship is taken into account to determine its significance. The calibration results are used to select sites for further analysis.

Multivariate analysis is used to investigate how varying basin characteristics impact the relationship between stream and air temperature. Basin characteristics data are collected based on the availability. Stepwise regression and principal component analysis are utilized across all of the well-calibrated sites. The basin characteristics are used as independent variables in these analyses to predict the parameters of the statistical stream temperature model. Finally, the multivariate analysis is used to develop a method for predicting the stream temperature model fit at an ungaged location.

3.1 Stream Temperature Data

This research contributes to a broader effort to consolidate existing stream temperature data from local, state, and federal agencies into a single database maintained by the Northeast Climate Science Center. This research focuses on data collected within New England and its use in model construction. The modeling effort utilizes continuous stream temperature data collected across New Hampshire, Massachusetts, Vermont, and Connecticut (Table 2). Most data were received in the form of an hourly time series, which was then aggregated to daily mean and maximum temperatures for model input.

Half of the sites have data for less than one calendar year and 75% have less than two years. While most of these sites have recorded summer stream temperature, many have seasonal data gaps. Only 39% of the 905 sites have recorded winter stream temperature, while 45% of the total sites are missing at least two seasons. Record length over the sites ranges from as low as one week up to nearly 12 years of continuous data monitoring. Both length of record and monitoring continuity are important to model calibration, which is discussed later in this section.

Agency	State	Number of Sites	Start Date	End Date
Massachusetts Fish and Wildlife (MFW)	MA	57	7/1/2005	11/10/2009
United States Geological Survey (USGS)	MA	8	5/14/1997	7/26/2012
New Hampshire Department of Environmental Services (NHDES)	NH	46	6/28/2006	10/20/2008
New Hampshire Fish and Game Department (NHFG)	NH	58	5/20/2005	11/23/2008
Connecticut Department of Environmental Protection (CTDEP)	CT	680	6/11/1998	5/2/2012
United States Forest Service (USFS)	VT	56	11/10/2010	10/3/2012
Total	-	905	5/14/1997	10/3/2012

Table 2: Stream temperature data source summary

3.2 Meteorological Data

Gridded, 1/8th degree, observed historic meteorological data, developed by Maurer et al. (2002), are used as the source of paired observed air temperature for most of the sites in the modeling effort. These data were used as they covered all of the sites of interest and could be aggregated to a watershed scale. The dataset includes maximum and minimum daily air temperatures for each grid cell, which are averaged to generate the estimated daily mean air temperature required for model input. The air temperatures are paired with stream temperatures based on the data points that lie within the contributing drainage area of the stream temperature site.

For each stream temperature data location, the upstream watershed is delineated using a series of computer scripts written in the R programming language which reference topological characteristics within the NHDPlus Version 2 (USEPA, 2010). Using the stream temperature site as the 'pour point' of the basin, the scripts locate all catchments upstream of the site and aggregate them into one contributing watershed. If multiple air temperature data points lie within this area, the temperature values are averaged into one value. If no meteorological data sites are present within the selected drainage area, the air temperature site nearest to the basin centroid is used. In this way, air temperature is paired to stream temperature for use in the nonlinear model. This process is repeated for all of the stream temperature sites except for a majority of those received from the USFS which already included observed air temperature paired over a consistent period of record.

3.3. Stream Temperature Model

As noted previously, air temperature is a primary driver of stream temperature. The air to stream temperature relationship may vary spatially, but has been established to typically be nonlinear (Mohseni et al, 1998). The relationship between stream and air temperature remains linear at mid-range temperatures (Figure 2). This relationship begins to change at the ends of the temperature spectrum. As air temperatures dip below 0 ^{o}C, the stream temperature reaches a freezing point, causing a discontinuity in the relationship. Most streams in the Northeast experience freezing air temperatures every winter, making this aspect important to capture. On the warm end of the range, the atmosphere's capacity to hold moisture increases with air temperature. The rate of evaporative cooling to the stream increases, causing another discontinuity. While a number of models use a simplified linear relationship between stream and air temperature, this research seeks to explore the uses of the nonlinear relationship.

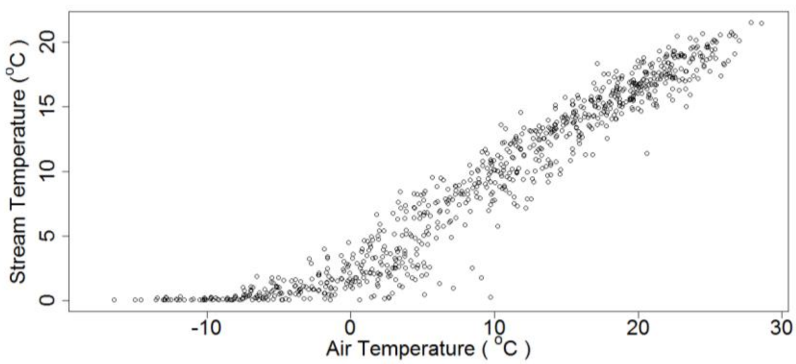

Figure 2: Air to stream temperature relationship of a river in western Massachusetts.

3.3.1 Nonlinear Regression Model Background

The nonlinear regression model used in this research was developed by Mohseni et al. (1998) and is constructed to replicate the stream-air temperature relationship year round. The nonlinear relationship mimics increased evaporative cooling at high temperatures and freezing at low temperatures. A logistic function is chosen because of the stability of its parameters and their pseudo-representation of physical properties. The function (Equation 1) requires the input of air temperature data (T_a). The parameters include estimated maximum stream temperature (α), air temperature at the inflection point (β), and the steepest slope of the function (γ) described by Equation 2, which includes the slope at the inflection point (tan θ). The estimated minimum stream temperature (μ) is also included to account for rivers that do not experience freezing. The functions may be applied separately to the rising and falling limbs of the air-stream temperature curve to account for the effects of hysteresis. Hysteresis is defined as the dependence of a system on the past environment as well as the present.

$$T_s = \mu + \frac{\alpha - \mu}{1 + e^{\gamma(\beta - T_a)}} \tag{1}$$

$$\gamma = \frac{4 \tan \theta}{\alpha - \mu} \tag{2}$$

Mohseni et al. (1998) applied the regression model on a weekly time step to 584 USGS stream gaging stations with air temperatures selected from the nearest of the 197 weather gaging stations. The model performed well with over 84% of all gaging stations having Nash-Sutcliffe Coefficient of Efficiency (NSC) values greater than 0.9. This NSC value is a common coefficient used to evaluate the prediction power in hydrologic models. Only 11 gaging stations (1.9%) were not well modeled by the S-shaped trend, having NSC values less than 0.7. Of these 11 stations, 8 are located downstream of reservoirs, which significantly impact natural stream temperature regimes. Correlation between the parameters and mean stream temperatures were minimal, leading to the conclusion that, given no physical changes to the watershed, parameters would not require adjustment under climate change. The study also concludes that air temperature data do not need to be obtained from locations in close proximity to stream gaging stations. The proposed model is limited to streams with S-shaped air to stream temperature relationships. When the relationship does not follow this trend, the model cannot explain the scatter of the data and is unable to accurately predict stream temperature. Mohseni et al. (1998) also note that the model occasionally under predicts maximum weekly stream temperatures. They state that in these cases, the model cannot be used to study the impact of climate warming on maximum weekly temperature.

For this research, the nonlinear model was chosen for its simplicity, performance, and wide acceptance amongst previous stream temperature modeling efforts. The model is easily constructed and applied to a large number of locations with stream temperature logger data. At locations where sufficient monitoring data and regular conditions exist, the model tends to perform well. The model is frequently used as a baseline in numerous stream temperature studies as well as being integrated into other models to fill in gaps of missing data, such as headwater temperatures (Morrill et al. 2005, Yearsley 2012). For the reasons stated above, the widely accepted non-linear regression model developed by Mohseni et al. (1998) serves as the foundation of the stream temperature modeling component of this research.

3.3.2. Model Calibration

The model described by Equation 1 is applied to all of the sites for which air and stream temperature data exist over a daily time step. The method described in the Meteorological Data section for pairing air temperature to stream temperature at each logger location is used for this model. The Shuffled Complex Evolution (Duan et al, 1992) global optimization method (SCE method) is used to fit the best parameters (α, β, μ, θ) for each dataset, yielding an optimal parameter set specific to each site. The SCE method is described as being efficient and effective procedure for computing optimal parameters in model calibration. This allowed all sites with a sufficient time series of paired stream and air temperature data to be fit with a model. Once the best fit parameters were calculated for each site, the sites were filtered for further analysis. A Nash-Sutcliffe Efficiency value of greater than 0.9 and a modeled temperature regime that visually displays a clear S-shaped fit (Figure 3) were required for the site to become a candidate for further evaluation. Due to the limited temporal extent of monitoring for most sites, the model is calibrated over the entire period of record for

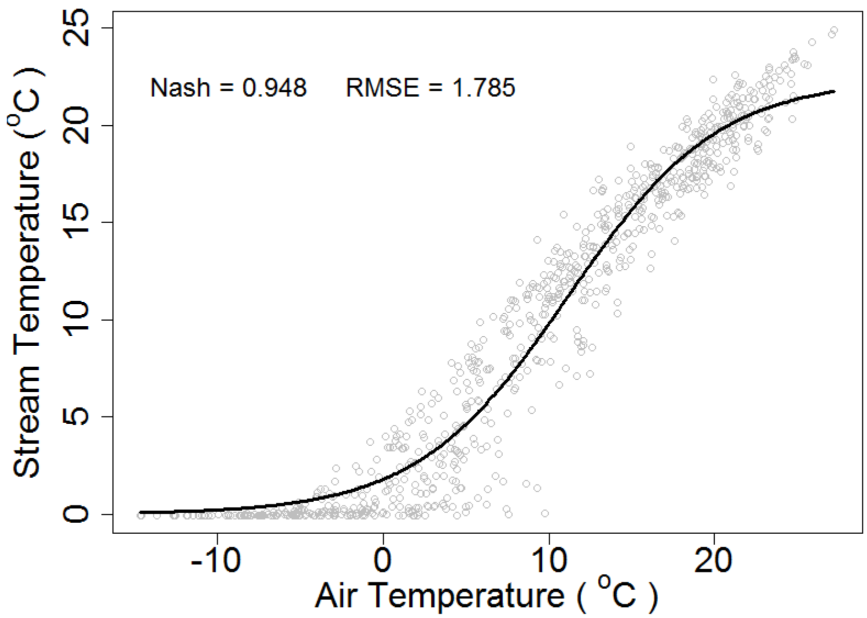

Figure 3: Well calibrated nonlinear model at a site in western Massachusetts.

each site. The best fit sites with sufficiently long periods of record are evaluated under a calibration and validation process. This process involves removing a portion of the data points at random, and recalibrating the model to the remaining points.

3.4. Basin Characteristics

Once the nonlinear stream temperature model was established for use, the next step was to select characteristics of the drainage area upstream of each temperature data site that might be influential to the stream temperature regime. A number of landscape variables were selected to determine which ones might be most influential to basins in the region. The variables were chosen with the goal of representing the range of possible factors in determining stream temperature regimes while maintaining an easily accessible source for the data. Many additional potential variables exist, but the ones chosen were deemed most likely be important to the stream temperature analysis, based on the literature reviewed. The incorporation of these variables into the modeling structure is described in the next section.

For each site that was deemed acceptable for further analysis, physical characteristics of the contributing watershed upstream of each site are aggregated using the delineated watershed (Section 3.2) Landscape attributes within the basin are calculated for each watershed. Table 3 provides a summary of watershed characteristics and sources of the GIS data from which the summary values are calculated. The Baseflow Index (BFI) is defined by the USGS as “the component of streamflow that can be attributed to groundwater discharge into streams” and is represented as percent of total flow (Wolock, 2003). The land use variables obtained from The Nature Conservancy's Ecological Systems Map were condensed into 10 major categories for the purpose of simplified analysis (Olivero & Anderson, 2008). “Total aboveground biomass” and “stem density” (> 1 inch diameter) contain information obtained from Dr. McGarigal’s research group in the Department of Environmental Conservation at the University of Massachusetts (Wilson et al., 1992). They are used in this research to represent forest cover in the watersheds.

Characteristic	Units	Source	Citation
Drainage Area	km^2	USGS - National Elevation Dataset	Gresch et al. (2009)
Topography:		USGS - National Elevation Dataset	Gresch et al. (2009)
Elevation	meters		
Slope	%		
Aspect	degrees		
Baseflow Index	%	USGS - GAGES II	Wolock (2003)
Soils:		USGS - GAGES II	Falcone (2003)
Sand	%		
Silt	%		
Clay	%		
Total Aboveground Biomass	tons/acre	FIA Imputations	Wilson et al. (1992)
Stem Density	Total/km^2	FIA Imputations	Wilson et al. (1992)
Land Use:		TNC - Ecological Systems Map	Olivero & Anderson (2008)
Urban	% of total		
Agriculture	% of total		
Swampland	% of total		
Grass	% of total		
Peat	% of total		
Rock	% of total		
Deciduous Forest	% of total		
Oak-Pine Mixed Forest	% of total		
Boreal Forest	% of total		
Open Water	% of total		
Historical Annual Averages (1980-2010):		PRISM Climate Group	PRISM (2012)
August Mean Air Temperature	^oC		
August Max Air Temperature	^oC		
August Total Precipitation	mm		
February Mean Air Temperature	^oC		
February Max Air Temperature	^oC		
February Total Precipitation	mm		

Table 3: Summary of data used for analysis.

3.5. Multivariate Analysis of Landscape Variables

A key element of this research is to identify key predictors stream temperature and develop relationships that are useful in predicting temperatures in ungaged basins. An understanding of these variables also enhances our understanding of what physical factors influence stream temperature, aiding in identifying streams that might be resilient to climate change and garnering conservation efforts targeted at maintaining biodiversity. In examining these relationships, the analysis seeks to integrate well-calibrated stream temperature models and physical landscape data to guide managers in their understanding of the watershed attributes that will impact stream temperature. First, a step-wise regression comparing the landscape variables with the fitted model parameters is run to determine any possible correlation between the two. A principal component analysis is then performed to further this analysis and draw conclusions about significant factors of stream temperature.

3.5.1. Stepwise Regression

The first method used to evaluate a regionalization approach of the parameters is a stepwise regression of the calibrated parameters. The stepwise regression is performed as a preliminary evaluation of which basin characteristics are most important in determining stream temperature, specifically their impact on each model parameter. This semi-automated method was chosen because of the large number of variables used for analysis. The results, a list of the most significant variables, are easily understood and discussed.

The stepwise regression process uses backward elimination, to remove variables based on their significance to each model parameter. A multivariate linear regression is run for each of the four parameters using all of the basin characteristics and locations. The basin characteristics are independent variables used as predictors of each parameter in the nonlinear model. The StepAIC function in the R statistical computation program performs the stepwise regression through matrix multiplication of all of the independent variables with all of the betas of the linear regression. The best relationships are chosen by minimizing the sum of the squared error terms. A limitation of this approach is that the error term is reduced with more predictors added, creating a case where the most predictors allowed are used. The Akaike information criterion (Equation 3) is used to counteract this case by penalizing the model for more predictors.

$$AIC = 2\,k - 2\ln(L) \tag{3}$$

Where:

AIC = Akaike Information Criterion

L = Sum of squared error terms

K = Number of predictors (independent variables)

If the mean value is the best fit, all of the predictors will be dropped, conversely if certain variables are identified as significant, they are assigned beta values in an equation used to predict the model parameter. A sensitivity analysis is applied to the completed stepwise regression models to determine which variables have the most influence over parameter values.

Stepwise regression overlooks correlation between variables. A correlation matrix of all basin characteristics used as variables was created with the purpose of determining if there is any false significance masked by a strong correlation between the variables themselves. This is presented in Appendix A. A principal component analysis is applied to the same data and used in a regression framework, as described below, to deal with the issue of multicollinearity.

3.5.2. Principal Component Analysis

PCA is traditionally used when correlation exists between variables or to condense large datasets with many variables to explore the principle mode of variation. PCA transforms correlated variables into uncorrelated variables called principal components. The process uses the correlation matrix of all of the variables and assigns weights (loadings) to the correlations based on Eigenvalue decomposition. Each set of loadings across the variables are a different principal component, with the total number principal components being less than or equal to the number of variables. Stronger correlations are more heavily weighted. The samples are multiplied by these loadings to get the scores, or the transformed values for each data point for each variable. Each principal component accounts for a portion of the variability within the data. The most variability is described in the first principal component and continues to decrease down to the last component. In cases where variables total one, such as land use or soil composition percentages, a variable is removed. In this case percent clay, boreal forest, and rock were chosen because of their relatively small values.

In this research, PCA is used for both exploratory analyses of the data, discussed here, as well as to predict stream temperature, described in the next section. The 23 landscape characteristics calculated for each basin are the variables used in the PCA. The PCA is run using all of the sites that meet the calibration criteria, 195 in total. Historic mean and maximum air temperatures during February and August are used to condition the regression for seasonal bounds. The results are used to illustrate which of the landscape variables are relevant to stream temperature.

3.5. Ungaged Basin Temperature Prediction

Stream temperature prediction at ungaged locations may be valuable in instances where a temperature estimate is needed, but data or access to the location is limited. Stream temperature prediction utilizing the PCA is explored and compared with other prediction methods. This comparison is used to determine the applicability of the PCA prediction method.

3.5.1. Principal Component Analysis

In addition to explaining which watershed attributes may impact stream temperature, the PCA is also used to generate a predictive stream temperature model. The calibration process initially yielded 160 sites across MA and CT that were deemed well-calibrated according to the criteria previously stated. The remaining 35 well-calibrated sites, from recently received data, are used to test the model.

Linear regression models using the principal components as predictors are created for each of the 4 calibrated parameters. These parameters act as the observations while the PCA scores serve as the independent variables. Principal components that have the most significance to each parameter are selected for the final models. Scores from these select PCAs are re-run to obtain the completed linear models for each parameter. These 4 completed models accommodate input of values for the 23 physical characteristics which are first standardized using the following equation:

$$SV = \frac{V - mean(C)}{std.dev.(C)} \tag{4}$$

Where:

SV = Standardized variable

V = Raw variable value

C = List of variable values across all prediction sites

The standardized values are multiplied by the respective loadings to produce prediction scores. These new scores are then multiplied by the corresponding betas in each model and summed according to the model to obtain the predicted parameter. These parameters are input into the nonlinear model equation with observed air temperature at a site to obtain a prediction of stream temperature data. This process is completed for the 35 validation sites and compared with two simpler prediction methods.

3.5.2. Mean Parameters

The mean parameters method simply takes an average of all of the parameter values across a number of sites, usually all of the sites within the same state as the site of interest. The averages of these parameters are then input into the nonlinear stream temperature model with observed air temperature at the site to generate predicted stream temperature time series.

3.5.3. Nearest Site Parameters

The nearest site approach to predicting stream temperature simply takes the parameters from the site that is the shortest distance from the site of interest. As is consistent with the other prediction methods, these parameters are input into the nonlinear model with observed air temperature at the site to predict stream temperature.

3.6 Breakpoint Analysis for Hysteresis

When analyzing the stream temperature regime it is necessary to understand the impact of hysteresis on the nonlinear distribution of stream temperatures at a location. Mohseni et al. (1998) account for hysteresis in their model by placing the data into two categories: the rising (warming) and falling (cooling) temperature limbs. The breakpoint where the time series is divided falls at a somewhat arbitrary point during the summer. This research devises a method to consistently select this point based on the data available with the goal of accurately capturing the impact of hysteresis on the distribution of the air to stream temperature ratio.

For the entire period of record at each site, a simple linear regression model is defined with stream temperature as the response and Julian day of year as the explanatory variable. Segmented regression is used to categorize the relationship in this model into the periods of rising and falling stream temperature. Nonlinear models are then fit separately to the rising and falling limbs of the air to stream temperature distribution. This version of the model is validated in the same way as the year-round model and incorporated into the stepwise regression to investigate how parameters may influence stream temperatures at different times of the year.

4. Results

The nonlinear stream temperature model is calibrated to each of the 905 stream temperature sites. 195 sites with the best calibration results are selected for further analysis. The sites with the longest record are used to validate the prediction power of the nonlinear model. The inclusion of hysteresis was found to provide negligible improvement to the model. After the nonlinear model is analyzed, it is utilized in multivariate analysis to inform which of the previously discussed basin characteristics impact stream temperature.

Results from the multivariate analysis show that alpha is predicted with the most accuracy and mu with the least. Model results for alpha, theta, and beta are good enough to allow conclusions to be drawn about each, potentially providing important information to natural resources managers. A sensitivity analysis of variables from the stepwise regression shows summer and winter air temperatures, forest coverage, soil properties, and elevation as being important to the air to stream temperature relationship. Principal component analysis results are summarized and examined more closely in the Discussion section. Results from the PCA prediction model validate this method as a viable method for predicting the nonlinear model parameters, but does not display improvement over simpler regionalization methods.

4.1. Nonlinear Model Calibration

4.1.1. Calibration

The nonlinear stream temperature model is fit to the full stream temperature record available for each site (905 sites across New England), using the SCE method to optimize model fit. Calibration results vary largely based on the period of record, seasonal distribution of data, and availability of paired air temperature data at a given site. Sites with observed stream temperature measurements spanning both warm and cold seasons and having consistent air temperatures tend to have the best calibration results. Given the variations in the data mentioned above, the initial

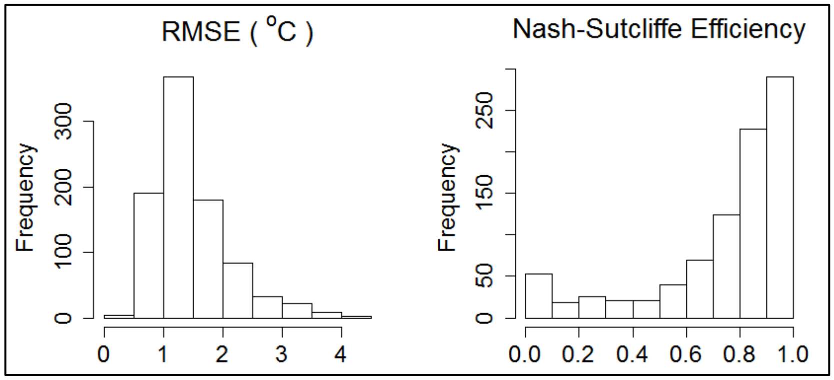

Figure 4: Distribution of calibration metrics for all 905 stream temperature sites.

calibration, which encompasses the full range of sites, is used to select the most appropriate sites for further analysis. The distribution of calibration metrics (NSC value and RMSE) is presented in Figure 4. 32% of the sites have an NSC over 0.9, 57% over 0.8, and 70% over 0.7. As mentioned in the Methodology section, the best sites for further analysis were chosen based on the criteria of an NSC above 0.9 and an S-shaped model fit to the data. This selection process yields 195 sites chosen for further analysis, which have an average NSC of 0.944 and RMSE of 1.55 ^{o}C. Many of the original sites, including all of those located in New Hampshire, were eliminated because of seasonal data gaps over the winter months. A handful of other sites were removed because of insufficient paired air

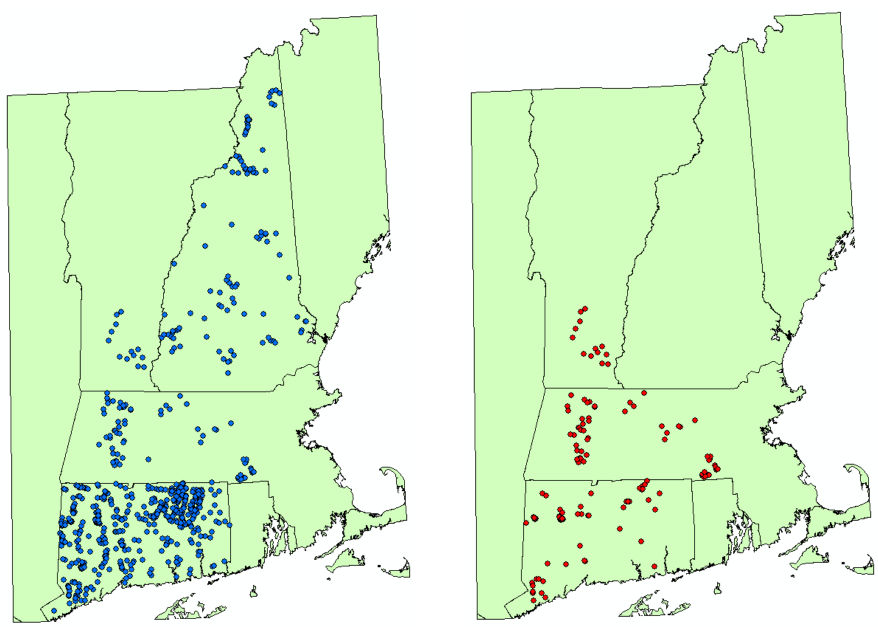

Figure 5: Locations of all 905 sites (left) and 195 best-fit sites (right).

temperature data. These were sites that did not already have paired air temperature and had most or all of their record after 2010, and thus were unable to be paired with the data from Maurer et al. (2007). Figure 5 shows the spatial distribution of all the stream temperature data locations.

4.1.2. Validation

A validation process is used to determine the ability of the nonlinear model to predict stream temperature. Twenty-six sites in Massachusetts with long periods of record (~3 years) are chosen for the validation process. At each site, one third of the stream temperature data are removed from the period of record and the model is calibrated to the remaining two thirds of the data. The new parameters are then used to validate the model to the removed temperature points. Calibration using two thirds of the data yields average values of 0.943 and 1.58 ^{o}C for NSC and RMSE, respectively. The same metrics for the validation process are 0.934 and 1.65 ^{o}C. A comparison of parameters from the calibration and validation results is shown in Figure 6. Figure 7 shows how the difference in parameters between the full period of record calibration and the validation is reflected in the Nash-Sutcliffe Efficiency. It is noted that in the validation process, as in standard calibration, a spread of data points across warm and cool seasons is critical to a good calibration. This aspect

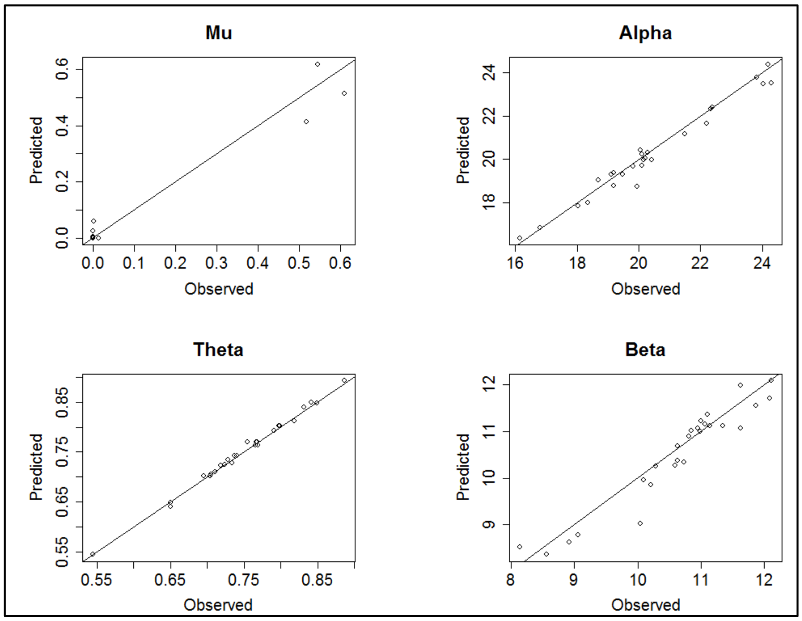

Figure 6: Nonlinear model validation results. "Observed" parameters are from the full period of record calibraiton and "Predicted" are from the validation process.

made a noticeably greater difference in model performance than the proportion of the sites removed for validation. The validation results confirm faith in the model's prediction power.

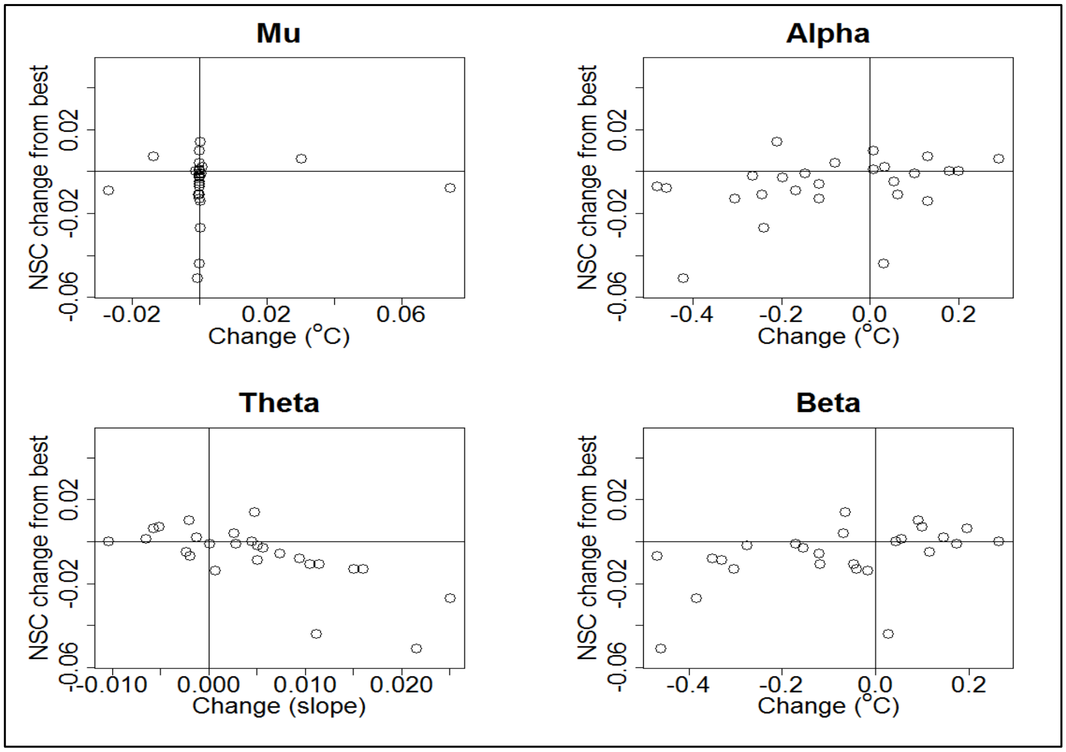

Figure 7: Changes from the standard calibration in parameters calculated in validation process.

4.1.3. Hysteresis

The same validation process is applied to the models developed from the breakpoint analysis that account for hysteresis. Using the methods described earlier for determining the rising and falling limbs of the stream temperature distribution, summer breakpoints are defined for 179 of the 195 well-calibrated stream temperature sites. Based on these breakpoints, nonlinear models are fit to the observed stream temperature over both rising and falling limbs (Figure 8). The warming period is from January 1st to the summer breakpoint, while the cooling period includes all points from the summer breakpoint until December 31st. Average calibration results for the rising, falling, and year-round models are summarized in Table 4. The inclusion of hysteresis provides only a minor change to the accuracy of the model.

Model	NSC	RMSE (°C)
Year-round	0.948	1.44
Rising	0.951	1.49
Falling	0.940	1.38

Table 4: Calibration metrics for model methods across the 179 sites with breakpoints.

The spread of nonlinear model parameters in these different methods shows some minor differences. Average mu and beta values remain about the same, while alpha values slightly increase for the falling limb. Theta increases for the rising limb and decreases for the falling

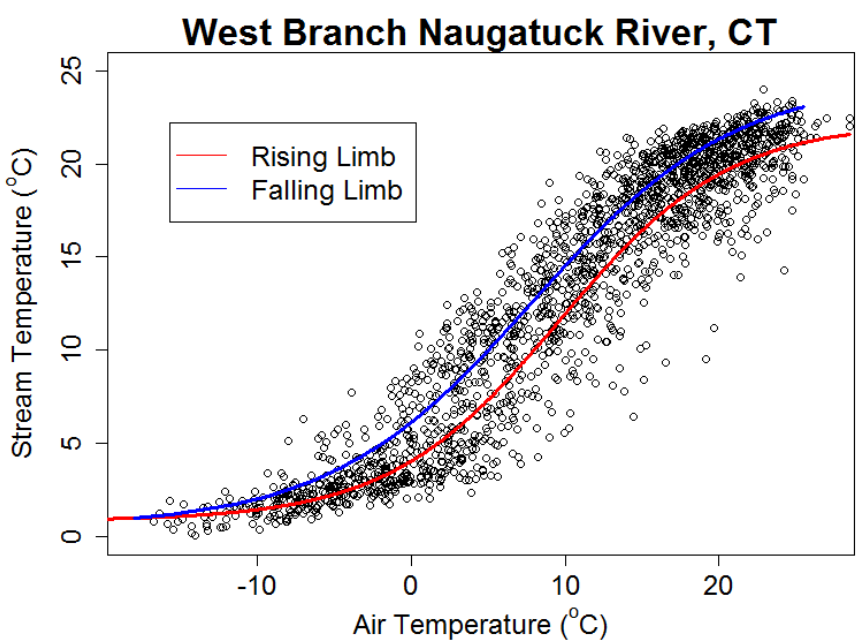

Figure 8: Example of a calibrated nonlinear model split into rising and falling limbs at a site in western CT.

limb of the hysteresis model. The parameter distributions are visually compared in Appendix C.

Validation is also applied to the hysteresis method over the previously selected 26 sites in MA with long periods of record. One third of the data points in each time series were removed and parameters were calibrated to the remaining two thirds of the data. Results of this process (Table 5) verify that the hysteresis method is viable; however it does not appear to improve the accuracy of the model by any significant degree. Accounting for hysteresis in the model does allow for the analysis of how landscape variables may separately impact the warming and cooling phases of stream temperature throughout the year, which is examined using stepwise regression in the next section. With the nonlinear model validated and the impact of hysteresis tested, multivariate analysis of the basin characteristics impact on model parameters can be investigated with the goal of providing useful information to resource managers. Understanding the factors that impact stream temperature regimes will allow for informed decisions on conservation efforts.

4.2. Multivariate Analysis

4.2.1. Stepwise Regression

The stepwise regression method is used to examine which physical properties influence stream temperature through a comparison of the complete-year, rising, and falling temperature model parameters regressed against basin characteristics. The adjusted R^2 values for the stepwise regression models for each model parameter are presented (Table 6). There is minimal difference in the prediction qualities

	NSC	RMSE (°C)
Year Round	0.939 (0.942)	1.61 (1.60)
Rising	0.929 (0.938)	1.47 (1.46)
Falling	0.947 (0.946)	1.36 (1.38)

Table 5: Calibration results of hysteresis model validation.

between the 3 nonlinear model types, aside from the decline of R^2 values for both alpha and theta in the falling limb models.

Model	Year-round	Rising	Falling
Estimated minimum temperature (μ)	0.248	0.256	0.236
Estimated maximum temperature (α)	0.546	0.490	0.320
Slope of the function at the inflection point (θ)	0.458	0.424	0.226
Temperature at the inflection point (β)	0.403	0.343	0.347

Table 6: Adjusted R^2 values for model parameters in the stepwise regression analysis.

The results from the stepwise regression comparison also show that there is limited deviation between the significant basin characteristics across the rising, falling, and year-round model fits. These results are shown in full in Appendix A. This may occur because a number of the variables used in the stepwise regression are correlated. A correlation matrix of these parameters is also available in Appendix A.

According to the stepwise regression, a positively correlated urban area remains the most significant factor of estimated minimum stream temperatures across all 3 model types. Its influence is twice as large in falling and year-round models as in the rising model, possibly because annual mean daily minimum temperature is not necessarily reached before the winter breakpoint on January 1st. Further investigation of the variation associated with the breakpoint is warranted. The consistently negative correlation with drainage area as well as the significance of soil type also suggests the influence of travel time and groundwater signal on minimum stream temperature. Prediction of this parameter is the least accurate (Table 6). The limited effectiveness of this parameter prediction is considered in the Discussion.

A sensitivity analysis is completed using the final stepwise regression models for the alpha, theta, and beta parameters to determine the sensitivity of each to changes in variable values. Mu is omitted from this analysis because of its poor prediction ability. The change on the three parameters is measured for the variables that were highlighted in the stepwise regression results (Appendix A). Tables 7-9 show the impacts of select variables on the parameters.

Quartile	Drainage Area	Stem Density	Deciduous Forest	Oak-Pine Mixed Forest	August Max Air Temp.
Min	-1.9%	9.8%	10.2%	14.1%	11.6%
Q1	-0.8%	1.1%	4.8%	13.5%	1.3%
Median	-	-	-	-	-
Q3	1.8%	-4.8%	-11.2%	-7.3%	-0.8%
Max	20.9%	-17.5%	-15.8%	-15.4%	-6.3%

Table 7: Sensitivity of the Alpha parameter to the five most influential variables.

Maximum stream temperature is consistently sensitive to drainage area and maximum August air temperature throughout the year (Table 7). Larger drainage area strongly indicates higher maximum stream temperatures. A counterintuitive relationship occurs in the negative correlation between August maximum air temperature and maximum stream temperature. The remaining three most influential variables are all related to forest coverage, and negatively correlated with maximum stream temperature, suggesting that shading plays an important role in determining stream temperature.

Quartile	Elevation	Deciduous Forest	Oak-Pine Mixed Forest	February Mean Air Temp.	February Max Air Temp.
Min	-19.5%	-14.3%	-13.6%	74.6%	-90.7%
Q1	-5.5%	-6.8%	-13.0%	19.9%	-15.8%
Median	-	-	-	-	-
Q3	5.9%	15.6%	7.0%	-5.2%	6.9%
Max	39.9%	22.1%	14.8%	-43.8%	61.0%

Table 8: Sensitivity of the theta parameter to the five most influential variables. Theta is nearly as sensitive to August maximum temperature and swampland as it is to the Oak-Pine forest.

Based on the sensitivity analysis, the slope of the function at the inflection point depends most on elevation, forest cover (deciduous and mixed oak-pine forests), and February temperature variables (Table 8). Increased elevation, forest coverage, and maximum February air temperatures all result in the air to stream temperature relationship being more nonlinear. Conversely, increased mean February air temperature results in a more linear function over all three models. Elevation loses significance in the rising limb model, while forest coverage does so in the falling limb. The consistent loss of significance in the falling limb by forest coverage may be an indication of the importance of shading to the system. In this period, deciduous trees drop their leaves and shading is reduced.

Quartile	% Sand	% Silt	August Mean Air Temp.	August Max Air Temp.	February Max Air Temp.
Min	-44.6%	-44.8%	-41.6%	63.2%	-61.1%
Q1	-13.1%	-3.1%	-7.4%	7.2%	-10.6%
Median	-	-	-	-	-
Q3	3.9%	14.6%	1.7%	-4.5%	4.6%
Max	52.2%	47.7%	23.6%	-34.1%	41.1%

Table 9: Sensitivity of the beta parameter to the five most influential variables.

The temperature at the inflection point depends most on the soil properties and air temperatures in both February and August (Table 9). Percent sand and silt both lose significance in the falling limb, indicating that groundwater influence over the mean temperature of stream system is greater in the spring and first half of summer.

The stepwise regression outlines some important variable-parameter relationships in the region. Sensitivity analysis is used to determine which variables have the most influence over the parameters. Summer and winter air temperatures, forest coverage, soil properties, and elevation stand out as being the most important variables to the air to stream temperature relationship. Principal component analysis is used to further explore the effects of watershed characteristics on stream temperature.

4.2.3. Principal Component Analysis

PCA is used to explore the modes of variability across watershed physical characteristics. Figure 9 presents the proportion of the total variance explained by each principal component using the basin characteristics of 195 calibrated sites. Over 70% of the variance is explained by the first four principal components. The first principal component (PC1) explains 44% of the total variance and is dominated largely by air temperature, soil type, and forest cover. Principal component 2 (~10% of the total explained variance) is governed by land cover types including swampland, agriculture, surface water, and peat land, as well as winter precipitation. A biplot is used to display the breakdown of variable significance on the combination of these two principal components (Figure 10). A biplot is a visual representation of the variable relationships of the first two principal componenets, which in this case explain 55% of the variance. The red arrows represent the loadings on each variable, which correspond to the bottom and left axes. The points represent the scores for each principal component. The angle between any two variables can be thought of as their correlation with each other. For example, in the biplot, air temperatures are highly correlated with each other. Linear models are fit using the PCs as the independent variables and each of the four nonlinear parameters. The PCs are uncorrelated by their nature (orthogonal in space) allowing all the PCs to be included in the regression if necessary. The parameter mu depends most on principal component 7, but the model fit for this parameter is poor. This issue is expored further the Discussion section. Principal components 1, 2, and 3 are the most influential predictors of alpha,

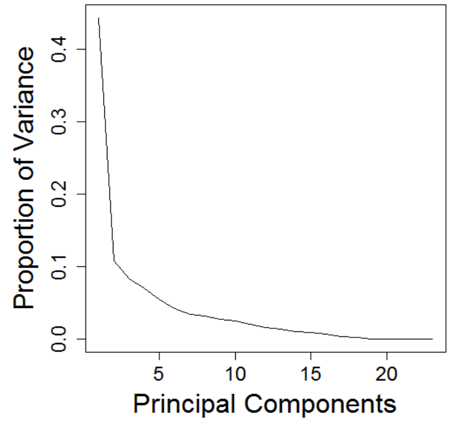

Figure 9: Proportion of variance explained by principal components.

while variability in theta is mostly explained by PCs 2 and 9. Model parameter beta is most strongly correlated with PCs 1, 3, and 5. Table 10 summarizes the most significant principal components and their loadings. The implications of these relationships are examined in the Discussion section. A complete summary of the PCA results can be found in Appendix B.

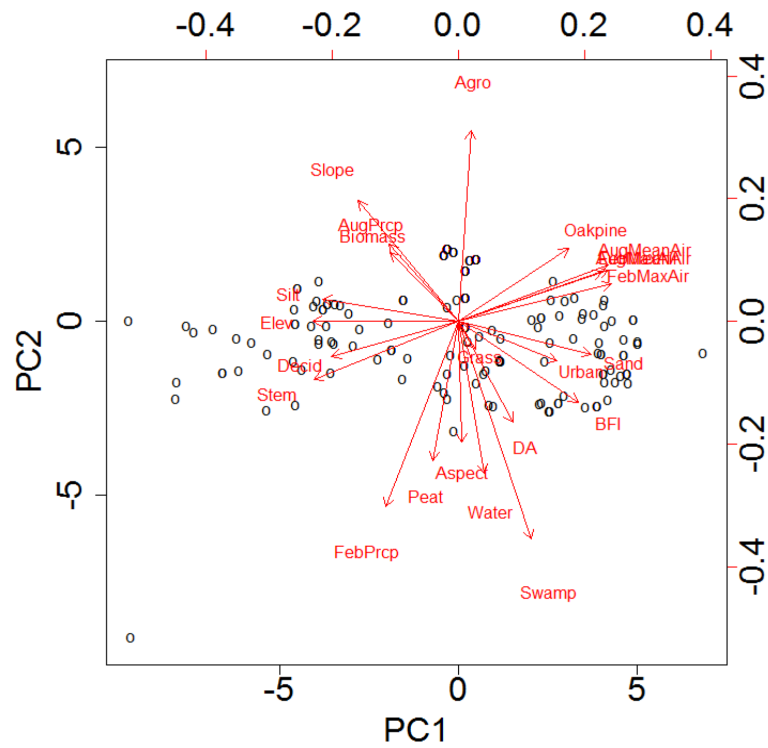

Figure 10: Biplot of principal components 1 and 2.

Rank	PC1 (44.3%)		PC2 (10.8%)		PC3 (8.3%)		PC5 (5.5%)		PC9 (2.7%)		PC12 (1.6%)	
1	FebMaxAir	0.303	Swamp	-0.443	DA	0.491	Grass	0.492	Urban	-0.5	DA	0.553
2	FebMeanAir	0.297	Agro	0.389	Water	0.381	Aspect	-0.421	Peat	0.486	Biomass	0.508
3	AugMeanAir	0.297	FebPrcp	-0.378	Biomass	-0.317	Urban	0.391	AugPrcp	-0.411	Sand	0.301
4	Elev	-0.288	Water	-0.31	Slope	0.276	Water	-0.286	Slope	0.35	Silt	-0.291
5	Stem	-0.287	Peat	-0.284	Grass	0.274	FebPrcp	0.27	AugMaxAi	0.199	AugPrcp	0.26
6	AugMaxAir	0.286	Aspect	-0.247	FebPrcp	-0.256	BFI	-0.261	Elev	-0.172	Decid	0.217
7	Silt	-0.27	Slope	0.246	BFI	-0.216	Oakpine	-0.242	Water	0.146	Oakpine	-0.2
8	Sand	0.263	DA	-0.205	AugPrcp	0.207	Peat	0.222	Oakpine	0.145	Peat	0.195
9	Decid	-0.252	BFI	-0.165	Sand	-0.202	AugMaxAir	0.152	FebMaxAi	0.143	Urban	-0.146
10	BFI	0.238	AugPrcp	0.157	Silt	0.185	Elev	-0.129	Sand	-0.132	FebPrcp	-0.144
11	Oakpine	0.218	Oakpine	0.148	Aspect	0.184	Stem	-0.118	AugMean/	0.13	Water	-0.096
12	Slope	-0.199	Biomass	0.14	Swamp	-0.164	Silt	0.104	Silt	0.125	Slope	0.079
13	Urban	0.196	Stem	-0.118	Urban	0.146	Sand	-0.092	Swamp	-0.114	Aspect	-0.078
14	Swamp	0.145	AugMeanAir	0.115	Agro	-0.144	AugPrcp	-0.085	Grass	0.1	AugMaxAir	0.042
15	FebPrcp	-0.144	FebMeanAir	0.105	Peat	-0.138	Decid	0.084	FebMean/	0.088	Elev	0.033
16	AugPrcp	-0.138	AugMaxAir	0.101	Stem	-0.058	FebMaxAir	0.065	Biomass	0.064	AugMeanAir	0.031
17	Biomass	-0.135	Urban	-0.081	FebMeanAir	0.037	Agro	0.048	Stem	0.056	Agro	-0.025
18	DA	0.107	FebMaxAir	0.076	AugMeanAir	0.035	DA	0.034	Decid	0.035	FebMaxAir	0.02
19	Water	0.05	Decid	-0.071	Decid	-0.032	Swamp	0.03	FebPrcp	0.027	Stem	-0.014
20	Peat	-0.05	Sand	-0.067	Oakpine	0.031	AugMeanAir	0.028	DA	-0.026	BFI	0.01
21	Grass	0.034	Grass	-0.056	AugMaxAir	0.027	Biomass	-0.027	Agro	-0.016	FebMeanAir	0.005
22	Agro	0.025	Silt	0.046	FebMaxAir	0.015	FebMeanAir	-0.012	BFI	0.016	Grass	-0.004
23	Aspect	0.007	Elev	0	Elev	-0.008	Slope	0.004	Aspect	0.007	Swamp	0

Table 10: Loadings in the important principal components for describing Mu, Theta, Beta, and Alpha.

4.3 Temperature Prediction

It is important to compare the temperature predictions of various regionalization methods to assess viability of predicting stream temperature at ungaged basins. The parameters calculated from the PCA prediction method are used to shape the nonlinear model to the observed stream temperature data (Figure 11). This is performed across the 160 sites used to calibrate the prediction model as well as the 35 sites used for validation. The results are compared with the mean and nearest site parameter prediction methods, as well as with the standard calibrated nonlinear model results (Figure 12). The comparison results validate the PCA prediction model as the best overall regionalization strategy. This prediction method provides the potential for future prediction of stream temperatures at a site without observed stream temperature. Further application of this model is described in the next section.

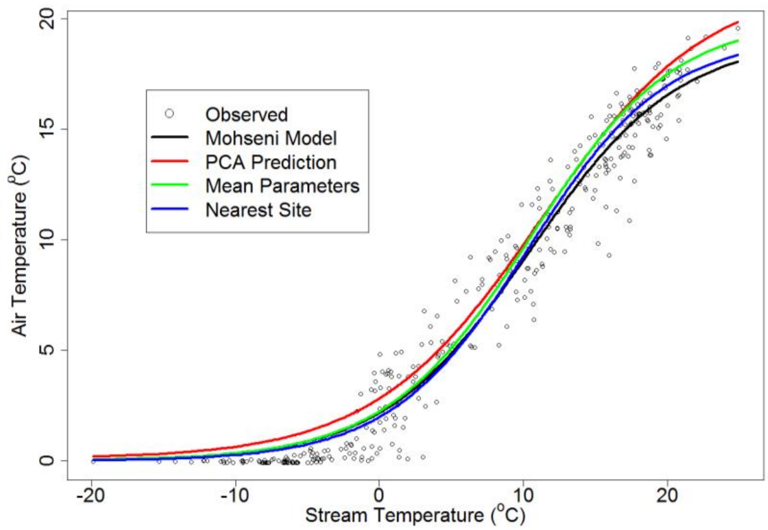

Figure 11: Stream temperature predictions for different methods at a site in western MA.

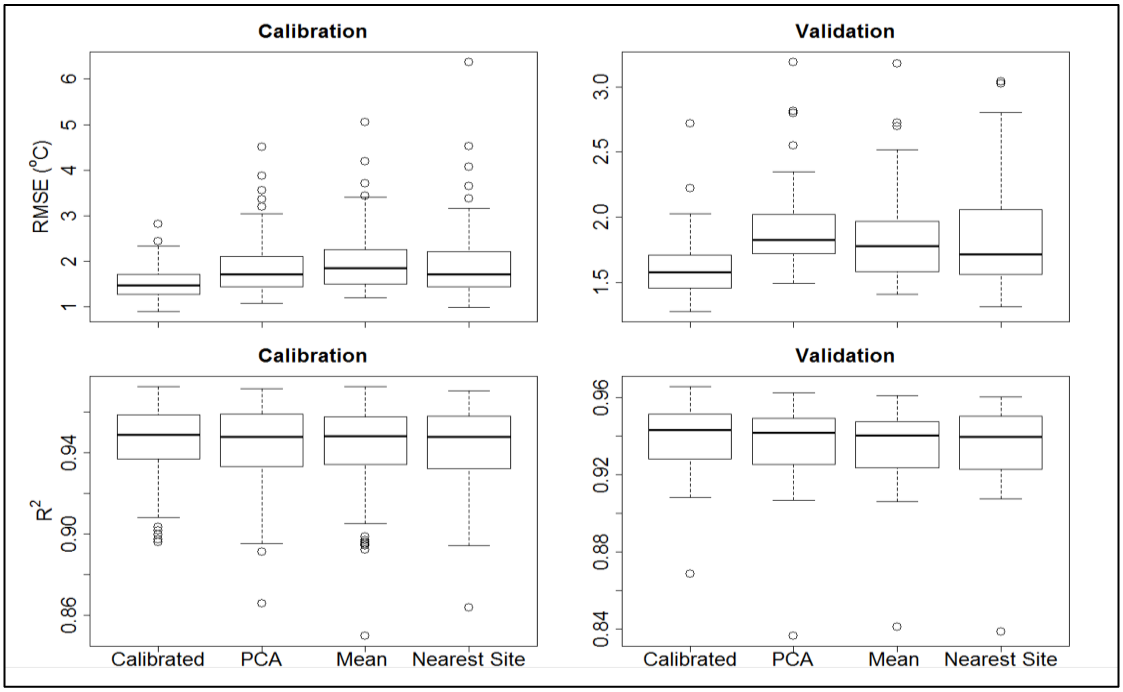

Figure 12: Calibration and validation results of the PCA stream temperature predication model.

5. Discussion

5.1. Physical Properties Impacting Stream Temperature

5.1.1 Principal Components

To understand the relationship between landscape characteristics and stream temperature, the most important principal components are examined. The important PCs are determined based on their influence over the quality of fit of the model, measured by adjusted R^2. Five principal components are individually evaluated by the weight of the landscape variables based on their loadings. This is done by describing each principal component as a watershed that may be characteristic of the most influential variables present. Analyzing the important variables that influence each mode of variation will help in understanding how they contribute to a particular parameter's effect on stream temperature.

Principal Component 1

Principal Component 1 is comprised of physical characteristics that would typically describe a warm, lowland watershed with limited forest coverage and a significant groundwater contribution to streamflow. This description is attributed to positive PCA loadings on air temperatures as well as percent sand and BFI and negative loadings on elevation, vegetation coverage, and percent silt.

Principal Component 2

Smaller, dryer basins with agriculture and small groundwater contribution appear to comprise principal component 2. Negative loadings on land cover classifications associated with surface water as well as historic February precipitation and BFI values explain this principal component. Large positive loadings exist on agriculture and average basin slope.

Principal Component 3

Principal component 3 is best described by large, open basins with more surface water and less groundwater and forest coverage. Positive loadings on drainage area, slope, surface water, and grassland and negative loadings on total aboveground biomass, BFI, and percent sand summarize this mode of variation.

Principal Component 5

Open or impervious land cover associated with less groundwater and more precipitation summarizes principal component 5. There are positive loadings on grassland, urban area, and winter precipitation, with negative loadings on surface water, BFI, and mixed oak and pine forests.

Principal Component 9

Principal component 9 can be described simply as low and likely wet areas with warm, dry summers. These basins may also contain some relatively steep slopes. Positive loadings on surface water and peatland and a strong negative loading on urban area suggest the land cover make up.

5.1.2. Estimated Maximum Stream Temperature (α)

The PCA regionalization regression explains 0.526 (R^2) of the variability exhibited in the alpha parameter (Figure 13). The variability of the alpha model parameter is explained by principal components 1, 2, and 3, having a positive relationship with all but PC 2. Examining the relationships with each principal component allows conclusions to be drawn about the impacts maximum stream temperature.

The description of basins common to principal component 1 is fairly consistent with higher maximum stream temperatures. Air temperatures, both in August and February, are found to have a positive correlation with alpha values. The relationship with August temperatures is straightforward as this is the time of year when temperatures are highest and hysteresis is more likely to affect the system.

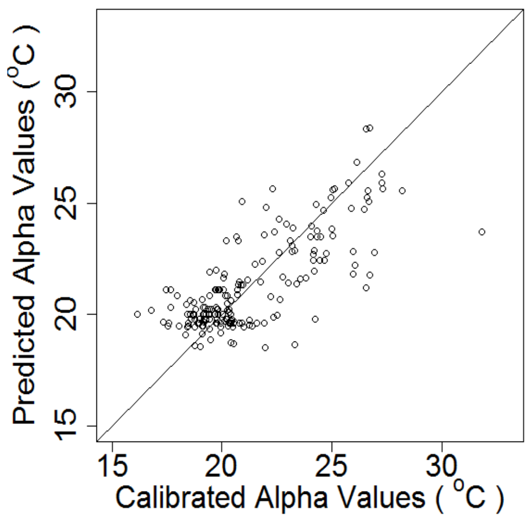

Figure 13: PCA regression model for alpha parameter.

The average summer breakpoint date of August 2nd supports this notion. The influence of elevation on maximum stream temperature can be attributed to the adiabatic lapse rate, where air temperature tends to decrease with increased elevation. This attribute translates to warmer air temperatures in basins at lower elevations, linking elevation to the relationship between air and stream temperature. The positive relationship with February air temperatures is slightly less obvious viewed in the context of the negative relationship between February precipitation and maximum air temperature. This relationship suggests the power of hysteresis over the system resulting from snowpack in the previous winter. The results seem to suggest that a warm, dry winter may result in a greater maximum stream temperature later in the year.

Surprisingly, the groundwater influence in this principal component seems to be positively correlated with stream temperature, disagreeing with the literature which defines groundwater as a moderating factor of stream temperature year round (Poole et al, 2001). It is possible that the variables representative of groundwater contribution, which exist as average values, impact the system at a different time of year than maximum stream temperature occurs.

This may also indicate that BFI is not a good index of groundwater's impact on stream temperature.

Finally, the limited forest coverage in the basins described by PC1 likely results in reduced shading to the system by riparian cover. The PCA results agree with those from the stepwise regression which has a negative correlation between alpha and forest coverage, specifically in the half of the year when temperatures are warming. This is supported by the findings of Bowler et al. (2012) which conclude from the literature that maximum stream temperatures are lower in systems with riparian shading than those without.

Principal component 2 is negatively correlated with estimated maximum stream temperature. The notion that small, dry, agricultural basins reduce maximum stream temperature can be supported by the idea that a shorter travel time does not allow the system to be exposed to climatic drivers long enough to be warmed as much as other basins. More rapid runoff over steeper slopes, and possibly from agriculture, as well as limited surface water explains this mode of variability. The rapid movement of the water through the system does not allow as much time to warm as basins with shallower gradients and more residence time in surface water sources. These findings are consistent with the concepts set forth by Mayer et al. (2012) and Subehi et al. (2009).

Principal component 3 has the most straightforward explanation. Large, open basins with surface water should theoretically have greater travel time in the system. This relationship is supported by the results from the stepwise regression which shows a positive correlation between alpha and drainage area across all three model types. In the summer months, this equates to greater heat energy flux into the system, which is further permitted by the reduced canopy coverage and shading associated with total aboveground biomass that is lacking in this type of watershed. Furthermore, the small groundwater influence eliminates another source of temperature moderation.

The stepwise regression and PCA results provide an understanding of the variables that impact the maximum stream temperature. Air temperature, particularly summer air temperature, plays an important role, remaining positively correlated with the alpha parameter. Drainage area is another notable variable that is positively correlated with maximum stream temperature. Groundwater influence appears to be influential to the alpha parameter, but has the opposite effect than expected. This may indicate that BFI is not a good measurement of the effect of groundwater on stream temperature. Finally, forest cover is a significant factor in determining maximum stream temperatures. Although some uncertainty exists in the PCA results, a majority of the analysis indicates that forest cover is negatively correlated with maximum stream temperature, supporting the idea that shading will reduce stream temperatures overall.

5.1.3. Slope of the Function at the Inflection Point (θ)

The theta parameter characterizes the slope of the nonlinear function at the inflection point and is one of the more informative parameters to resource managers. Theta determines the degree of nonlinearity of the air to stream temperature relationship. A greater theta

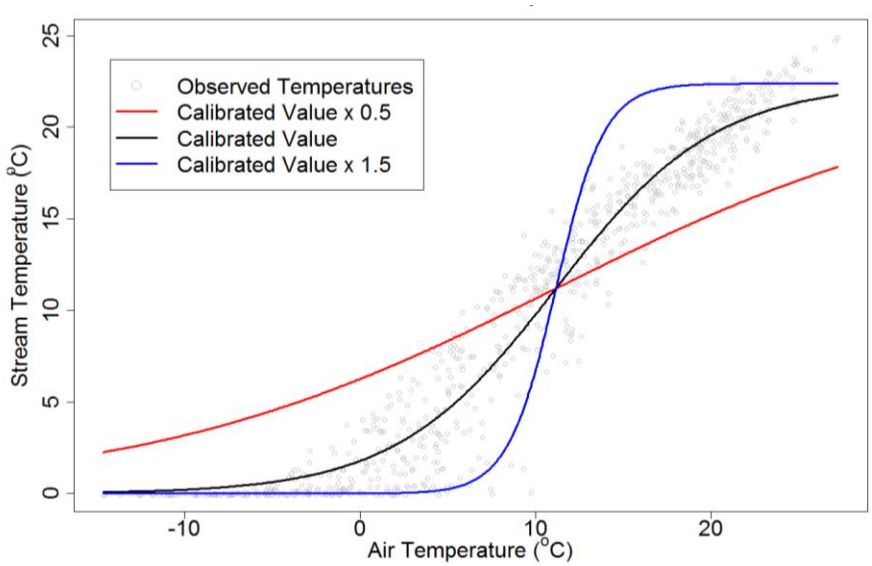

Figure 14: Example of varied theta parameter on the nonlinear model function.

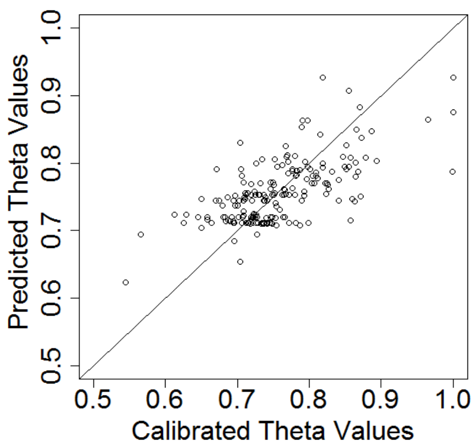

Figure 15: PCA regression model for theta parameter.

value decreases the linearity of the relationship and the presence of a top and bottom threshold at which stream temperature undergo a change over just a few degrees of air temperature (Figure 14). It can be inferred that principal components with a negative correlation with this parameter produce a more linear relationship. If the fit to the relationship is good, linearity suggests that air and stream temperatures are in sync for a longer period of time. Variables with a positive correlation with theta indicate a stream temperature influence external to the air temperature relationship, such as groundwater or thermal influx from anthropogenic sources. The predictive power of this model had an adjusted R^2 of 0.370 and the modeled vs. observed values are plotted in Figure 15.

Both of the principal components in the regression have a negative relationship with theta, suggesting that basins typical to these PCs will result in a more linear air to stream temperature relationship. The small, dry basins of PC2 have less groundwater inflow which supports the notion of increased function linearity. Lower February precipitation, indicating reduced snowpack, indicates a weaker mode of hysteresis coming out of the winter season, which translates to a more linear relationship. The lack of surface water such as lakes, ponds, and swampland could mean a more constant exposure to climatic drivers, particularly air temperature, which will also keep the relationship more linear. This last relationship is in agreement with the stepwise regression which shows a significant, positive correlation between swampland and theta.

Principal component 9 has the same impact on function linearity, despite the fact that it differs from PC2 in that it is more likely to have more surface water. The large negative loading on urban area however indicates that nonlinearity may be intensified by anthropogenic input. The strong correlation of non-linearity of the function with August precipitation should also be noted.

Winter meteorological conditions, elevation, groundwater, and forest coverage are important variables in determining the linearity of the air to stream temperature relationship. Correlations with some of these factors, particularly winter temperatures, vary. A consistent exposure to air temperature with minimal interference from other drivers indicates linearity of the relationship. This parameter is important to understanding how the stream temperature regime in a basin might react to anthropogenic changes such as urbanization or deforestation.

Knowing the factors that affect the linearity of the air/stream temperature relationship can be helpful to natural resource managers assessing the impacts of climate change. Streams with limited external temperature drivers are likely to have a more linear relationship meaning that increased air temperatures will be more influential over the stream temperature regime. This information is important in determining conservation targets of a particular fish located in watersheds characteristics impacting theta. One hypothetical situation might be the presence of brook trout in a watershed with a strong nonlinear relationship (larger theta). If air temperatures are predicted to increase where incipient stream temperatures are likely to be reached more frequently, this research would suggest conservation efforts focus on protecting groundwater sources and shading in this basin. Furthermore, a comparison of theta values and the relevant basin characteristics between watersheds would allow efforts to focus on one basin over another. Knowledge of the factors impacting the linearity of the air to stream temperature relationship can be used by resource managers to aptly define conservation targets.

5.1.4. Temperature at the Inflection Point (β)

The beta parameter is the air temperature at the inflection point. This value represents a shift in the mean water temperature of a stream. A lower beta value indicates stream system which will begin warming at lower air temperatures. Higher beta values indicate a tendency of the stream system to remain at a cooler temperature and will require much higher air temperatures to warm the stream (Figure 16). The beta values can also be an indication of how hysteresis impacts the rising and falling limbs of the function. Under the rising and falling limb models, an increased beta value will emphasize hysteresis on the cool end of the temperature spectrum, while a decreased value will suggest stronger hysteresis on the warm end.

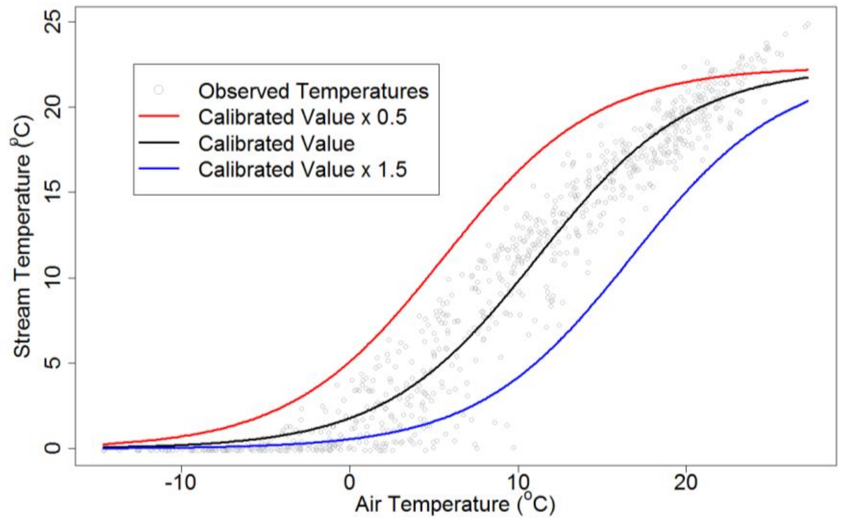

Figure 16: Results of varied beta parameter on the nonlinear model function.

Watersheds typical of principal components 1, 3, & 5 all appear to have a strong positive correlation with beta, indicating that they have a tendency toward cooler overall stream temperatures. The predictive power of this model

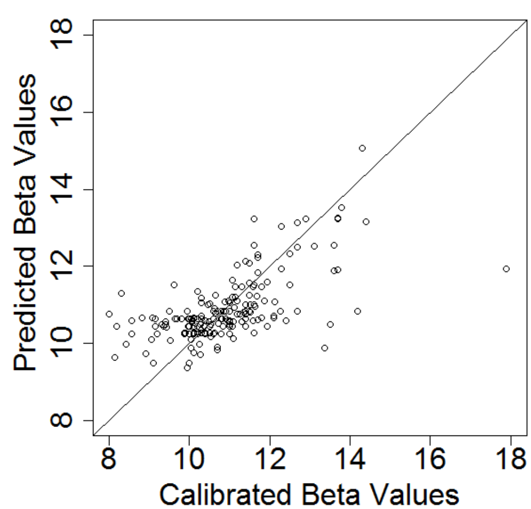

Figure 17: PCA regression model for the beta parameter.

had an adjusted R^2 of 0.320 and the observed versus modeled values from the regression are shown in Figure 17.

Principle component 1 does not seem to agree with the stated effect of beta, lowland basin with warm air temperatures would not contribute to cooler average stream temperatures. The strong groundwater component however, may be the most important variable, keeping stream temperatures cool despite warming air temperatures. Additionally, limited surface water bodies would mean reduced travel times, and relatively short exposure to heat flux into the system. Without these features in the basin, there are fewer sources that would continue to contribute warmer temperature as air temperature decreases.

The other two principal components differ in that they both have a less significant groundwater component. PC 3 suggests that increased drainage area, more surface water and less biomass and February precipitation are conditions that will require warmer air temperatures to heat the stream system. This leads to some uncertainty as to what features in this mode of variation may contribute to warmer basin temperatures. In principal component 5, the lack of surface water and increased February precipitation somewhat agree with the notion that these systems will require warmer air temperatures to heat the system. The relatively open landscape (more grassland and urban area), which might suggest warmer system, causes more confusion with this parameter.

Initial results from the stepwise regression show that groundwater is clearly a prominent variable, with both sand and silt being positively correlated with beta. This might support that idea that basins with more groundwater influence require warmer air temperatures to heat the system, but the uncertainty behind the groundwater and soil property relationship limits the conclusions that can be drawn. This analysis also shows that beta seems to increase with higher mean summer air temperatures, but decrease with higher maximum summer air temperatures. Overall, the factors contributing to the beta parameter are the least understood from this analysis.

5.1.5. Estimated Minimum Stream Temperature (μ)

The PCA results for estimated minimum stream temperature showed minimal predicative power. The adjusted R^2 of the linear model was 0.038, making the model of no value in parameter prediction. Of the 195 sites included in the PCA, 181 had mu values less than 0.1^oC and 8 more had values under 1^oC. The poor fit is likely due to streams in the region having minimum mean daily temperatures around 0^oC. Only 3 of the sites with non-zero estimated minimum stream temperatures fall outside of the state of Connecticut. While it is unfortunate that there is little to be said about the landscape variables that may impact minimum stream temperatures, it is relatively safe to assume that mu can be predicted as 0^oC across the northeast region, with greater confidence outside the southern-most states. Results from both the stepwise regression and PCA agree that urban area coverage increases the minimum stream temperature. However, model results cannot be relied on because of the poor fits and further analysis of the impact of urban area on minimum stream temperature is needed before conclusions may be drawn.

5.2 PCA Stream Temperature Prediction Model

The stream temperature prediction model developed using PCA has potential for use in areas where observed stream temperature data may be limited. The physical properties included in the prediction model are relatively easily obtained over a large scale area. Utilizing these existing data to drive the model at an ungaged site is significantly less time consuming and labor intensive than gage installation at the desired location. The method developed may be useful for situations where an estimate of stream temperature is needed on a daily or weekly timescale.

This is the case in the application of one physical stream temperature model (Yearsley, 2011), where the nonlinear model is used to determine initial conditions for the physical model at headwater locations. The model is simple to construct and, providing sufficient coverage of sites throughout the region of interest, predicts stream temperature at a level of accuracy comparable to that of the nonlinear model calibrated to observed temperature.

The model may also be used to assess the impacts of anthropogenic changes to stream temperature regimes in the region. Climate change and urbanization are likely to be the major contributors to temperature regime change in the future. Understanding how these factors impact stream temperature will be critical in assessing which watersheds may be more resilient to changes.

6. Conclusion

Stream temperature regimes are dependent upon physical processes influencing the hydrology of the watershed. These processes fall into the groupings of climatic drivers, groundwater influence, riparian vegetation, land use in the basin, and channel morphology. As stream temperature is a crucial factor of ecosystem health, understanding these factors is critical step to understanding how changes to the system may impact ecosystem vulnerability.

A nonlinear stream temperature model developed by Mohseni et al. (1998) is applied to 905 sites throughout the northeastern US, yielding 195 sites appropriate for further analysis. The average NSC for the nonlinear model across 195 sites is 0.948. Accounting for hysteresis in the system returns NSC values of 0.951 and 0.940 for rising and falling limbs, respectively. A principal component analysis and stepwise regression are performed on each of the 4 calibrated nonlinear model parameters against 23 landscape variables with the purpose of determining which watershed characteristics may be significant factors in determining the stream temperature regime.

Five principal components are defined as having the most significant influence over stream temperature regimes in the region. Not surprisingly, mean and maximum air temperatures showed a strong correlation with the parameters, particularly estimated maximum temperature. Temperature significance of winter temperatures and precipitation on this parameter suggests hysteresis in the systems, possibly resulting from the annual snowpack.

Interpretation of the regression results also points to groundwater as an important factor on stream temperature regimes, although the results seem to show mixed signals on how it will impact maximum temperatures. This inconclusiveness is not surprising due the difficulty in accurately quantifying groundwater in hydrologic systems. The most that can be said about groundwater from this research is that it possibly contributes to hysteresis on the cooler end of the temperature spectrum, however further research is required to make any definitive statements.

Exposure to solar radiation, specifically resulting from travel time (drainage area and slope) and perceived degree of shading, supports the findings from the reviewed literature. Increased forest cover, measured by total aboveground biomass, stem count, and forest type is found to be correlated mostly with reduced maximum stream temperatures. Travel time is also positively associated with this parameter, suggesting longer exposure to climatic drivers increases the maximum stream temperature. A consistent, uninterrupted exposure to these drivers may also mean a more linear relationship between air and stream temperature.

Finally, increased urban area coverage is found to increase non-linearity of the model function. The specific sources are not covered in this research and further investigation will be required to understand the precise impacts of different factors associated with urban development on stream temperature. A more nonlinear air to stream temperature relationship was also found to be associated with the presence of more drivers external to air temperature, mainly forest coverage and groundwater influence. This information is useful in defining conservation targets, specifically which basin characteristics to protect in certain basins.

Based on this research, changes to any of the significant variables (air temperature, groundwater, shading, travel time, and urban area) in a watershed are likely to result in alteration of the stream temperature regime. Climate change, logging, land development, and streamflow regulation are just some of the possible anthropogenic influences that target these vulnerabilities. Preservation of biodiversity in the Northeast riverine systems depends upon the understanding and accounting for how human action will impact these stream temperature variables.

7. Future Work

This research has generated some insight on the continuation of effort to understand stream temperature. Further studies, including a specific analysis of urban area and riparian coverage in the region, would be helpful in understanding their impact on stream temperature. The literature is virtually unanimous that increased urban area increases stream temperature and riparian canopy coverage maintains the natural regime. While this analysis touches on these variables, more specific data included in the analysis performed in this research may provide valuable information on how these factors impact aspects of the stream temperature regime. A better estimate of groundwater contribution and the inclusion of flow-rate are two more variable additions that would likely improve results. Potential exists in exploring the impact of urban development on the minimum stream temperature parameter (mu). The study area of this research did not have enough variation among this parameter to generate reliable results. Utilizing similar stream temperature data from warmer climates may lead to a conclusion about this relationship. Both the model structure and data are available to the Northeast Climate Science Center to undertake this expansion.

Finally, prediction power of the nonlinear model itself may have room for improvement. The current model predictions are not accurate enough for some applications, such as use in biological models. Further development of the breakpoint analysis methodology may improve results. Splitting the year into phases where temperature is either "in sync" or "out of sync" with air may be explored. The "out of sync" phase refers to the time of year when the air temperature continues to drop, while stream temperature remains consistent around 0^oC due to freezing. Addressing these differing phases may be one key to improving model prediction power.

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Appendix A: Stepwise Regression Results

A1. Year-round Model

Significance codes:	
0	'***'
0.001	'**'
0.01	'*'
0.05	'.'
0.1	' '

Mu					
	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	29.07495	14.05592	2.069	0.04011	*
DA	-0.00735	0.003056	-2.405	0.01723	*
Sand	-0.3012	0.141465	-2.129	0.03469	*
Silt	-0.31849	0.161519	-1.972	0.05026	.
Stem	-0.00011	6.54E-05	-1.738	0.08396	.
Urban	0.06747	0.010336	6.528	7.49E-10	***
Decid	0.026906	0.008226	3.271	0.0013	**
Oakpine	0.027353	0.008557	3.197	0.00166	**
AugMeanAir	-0.19864	0.128131	-1.55	0.12294	
FebPrcp	0.027639	0.009907	2.79	0.00588	**

Alpha					
	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	41.46315	8.521978	4.865	2.59E-06	***
DA	0.057073	0.009927	5.749	4.07E-08	***
Sand	0.141768	0.04075	3.479	0.000639	***
Stem	-0.0005	0.00017	-2.948	0.003647	**
Agro	-0.13244	0.02908	-4.554	9.98E-06	***
Grass	1.62248	0.655323	2.476	0.014271	*
Decid	-0.05646	0.016321	-3.459	0.000685	***
Oakpine	-0.07661	0.015974	-4.796	3.52E-06	***
AugMaxAir	-0.70978	0.316918	-2.24	0.02641	*

Theta					
	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	0.979311	0.702331	1.394	0.165091	
DA	0.001273	0.000313	4.063	7.49E-05	***
Elev	0.000587	0.000148	3.962	0.000111	***
Slope	-0.00793	0.00182	-4.36	2.29E-05	***
Sand	-0.00217	0.001499	-1.444	0.150522	
Urban	0.002397	0.001059	2.264	0.024872	*
Swamp	0.00968	0.001669	5.802	3.30E-08	***
Grass	0.066068	0.020467	3.228	0.001506	**
Peat	-0.04289	0.028606	-1.499	0.135744	
Decid	0.00268	0.000795	3.372	0.00093	***
Oakpine	0.0025	0.000828	3.018	0.002948	**
AugMaxAir	-0.03798	0.027148	-1.399	0.16374	
FebMeanAir	-0.10709	0.01701	-6.296	2.69E-09	***
FebMaxAir	0.168549	0.031416	5.365	2.72E-07	***
FebPrcp	-0.00219	0.001033	-2.124	0.035153	*

Beta					
	Estimate	Std. Error	t-value	Pr(>|t|)	
(Intercept)	-4.43339	30.21075	-0.147	0.88351	
Elev	-0.00506	0.003041	-1.662	0.09837	.
BFI	-0.14277	0.051046	-2.797	0.00579	**
Sand	0.464456	0.248638	1.868	0.06358	.
Silt	0.51074	0.28559	1.788	0.0756	.
Urban	0.024246	0.013762	1.762	0.08	.
Agro	-0.03574	0.01555	-2.298	0.02282	*
Swamp	0.060322	0.027516	2.192	0.0298	*
Grass	0.676413	0.359882	1.88	0.06198	.
Peat	0.879292	0.500309	1.757	0.08073	.
Oakpine	-0.01706	0.005348	-3.19	0.00171	**
Water	-0.10873	0.06905	-1.575	0.11731	
AugMeanAir	1.118273	0.713335	1.568	0.11892	
AugMaxAir	-1.98136	0.650269	-3.047	0.0027	**
AugPrcp	0.036202	0.014754	2.454	0.01521	*
FebMeanAir	-0.88819	0.616888	-1.44	0.15187	
FebMaxAir	1.725553	0.632035	2.73	0.00704	**
FebPrcp	-0.038	0.019348	-1.964	0.05124	.

A2. Rising Limb Model

Mu					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	2.11E+01	1.30E+01	1.614	0.10833	
DA	-9.38E-03	3.34E-03	-2.805	0.00563	**
Sand	-2.94E-01	1.43E-01	-2.063	0.04063	*
Silt	-3.19E-01	1.62E-01	-1.965	0.05108	.
Stem	-1.29E-04	7.49E-05	-1.718	0.08771	.
Urban	3.95E-02	9.15E-03	4.317	2.70E-05	***
Agro	-3.00E-02	1.17E-02	-2.572	0.01097	*
Swamp	-3.61E-02	1.54E-02	-2.352	0.01986	*
AugMaxAir	2.85E-01	1.71E-01	1.668	0.09718	.
FebPrcp	2.69E-02	9.87E-03	2.722	0.00718	**
FebMaxAir	-3.37E-01	1.71E-01	-1.974	0.05002	.

Alpha					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	64.48652	19.25715	3.349	0.001003	**
DA	0.056253	0.012053	4.667	6.24E-06	***
Elev	-0.0124	0.005589	-2.218	0.027882	*
Sand	0.078173	0.048369	1.616	0.107942	
Agro	-0.10948	0.032762	-3.342	0.001028	**
Grass	2.783318	0.739922	3.762	0.000233	***
Peat	1.70481	0.963212	1.77	0.078565	.
Decid	-0.07176	0.019756	-3.632	0.000374	***
Oakpine	-0.09642	0.020208	-4.772	3.96E-06	***
AugMaxAir	-1.4254	0.646191	-2.206	0.02876	*
AugPrcp	0.043157	0.028461	1.516	0.131323	
FebPrcp	-0.06358	0.035806	-1.776	0.077631	.

Theta					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	2.14E+00	7.74E-01	2.758	0.006465	**
DA	6.46E-04	3.46E-04	1.867	0.063714	.
Slope	-9.44E-03	2.03E-03	-4.646	6.88E-06	***
BFI	-5.07E-03	2.65E-03	-1.913	0.057426	.
Stem	1.52E-05	7.56E-06	2.015	0.04557	*
Swamp	1.06E-02	2.03E-03	5.249	4.65E-07	***
Grass	6.51E-02	2.35E-02	2.769	0.006271	**
Decid	2.14E-03	8.38E-04	2.551	0.011665	*
Oakpine	1.40E-03	8.63E-04	1.625	0.106067	
AugMaxAir	-6.75E-02	2.86E-02	-2.358	0.019551	*
AugPrcp	2.90E-03	8.96E-04	3.238	0.001457	**
FebMeanAir	-6.28E-02	1.72E-02	-3.66	0.000339	***
FebMaxAir	1.30E-01	3.37E-02	3.871	0.000156	***
FebPrcp	-3.77E-03	1.05E-03	-3.586	0.000442	***

Beta					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	-1.48E+01	3.65E+01	-0.405	0.68564	
Elev	-9.31E-03	3.48E-03	-2.676	0.008202	**
Slope	1.89E-01	4.01E-02	4.706	5.30E-06	***
BFI	-2.40E-01	6.62E-02	-3.622	0.000388	***
Sand	6.06E-01	2.95E-01	2.054	0.041589	*
Silt	6.32E-01	3.39E-01	1.865	0.063889	.
Stem	2.10E-04	1.52E-04	1.384	0.168215	
Grass	9.19E-01	4.80E-01	1.914	0.05728	.
Peat	1.13E+00	5.55E-01	2.035	0.043419	*
Decid	-6.79E-02	1.54E-02	-4.409	1.86E-05	***
Oakpine	-7.50E-02	1.68E-02	-4.464	1.48E-05	***
AugMeanAir	1.50E+00	4.67E-01	3.212	0.001582	**
AugMaxAir	-1.78E+00	6.63E-01	-2.689	0.007908	**

A3. Falling Limb Model

Mu					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	33.81141	14.3028	2.364	0.0192	*
DA	-0.00825	0.003213	-2.566	0.01113	*
Sand	-0.38843	0.148357	-2.618	0.00963	**
Silt	-0.41147	0.168252	-2.446	0.01548	*
Urban	0.06492	0.009768	6.647	3.86E-10	***
Decid	0.018418	0.007396	2.49	0.01371	*
Oakpine	0.017789	0.007467	2.383	0.01829	*
FebPrcp	0.024346	0.009398	2.591	0.01041	*

Alpha					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	-6.60E+01	6.62E+01	-0.996	0.3206	
DA	7.16E-02	1.49E-02	4.807	3.38E-06	***
Sand	1.35E+00	6.81E-01	1.989	0.0484	*
Silt	1.41E+00	7.73E-01	1.822	0.0703	.
Stem	-4.47E-04	2.51E-04	-1.781	0.0768	.
Urban	6.76E-02	3.87E-02	1.744	0.083	.
Swamp	1.78E-01	6.90E-02	2.578	0.0108	*
Peat	1.87E+00	1.30E+00	1.44	0.1517	
Oakpine	-1.60E-02	1.09E-02	-1.474	0.1425	
AugMaxAir	-1.13E+00	4.76E-01	-2.367	0.0191	*
FebPrcp	-1.38E-01	5.41E-02	-2.555	0.0115	*

Theta					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	0.726406	0.223674	3.248	0.001404	**
DA	0.001349	0.000485	2.783	0.005992	**
Elev	0.000576	0.00017	3.381	0.000898	***
Slope	-0.00723	0.002633	-2.746	0.006689	**
Sand	-0.00526	0.00232	-2.269	0.024545	*
Swamp	0.007801	0.002517	3.1	0.002269	**
Grass	0.081735	0.032441	2.519	0.01268	*
FebMeanAir	-0.0867	0.024385	-3.556	0.000489	***
FebMaxAir	0.115066	0.036303	3.17	0.001812	**

FebPrcp	-0.00485	0.00142	-3.415	0.000799	***

Beta					
	Estimate	Std. Error	t-value	Pr(>|t|)	Signif.
(Intercept)	69.58743	16.27011	4.277	3.18E-05	***
DA	0.010383	0.007477	1.389	0.166783	
BFI	-0.20683	0.065175	-3.173	0.001794	**
Sand	0.07495	0.041215	1.819	0.070773	.
Urban	0.031469	0.0182	1.729	0.08564	.
Swamp	0.124122	0.036891	3.365	0.000951	***
Decid	0.022087	0.007337	3.01	0.003014	**
AugMeanAir	1.609647	1.040105	1.548	0.123616	
AugMaxAir	-3.73698	0.876142	-4.265	3.33E-05	***
FebMeanAir	-1.9015	0.881902	-2.156	0.032504	*
FebMaxAir	4.037484	0.875952	4.609	7.99E-06	***
FebPrcp	-0.0496	0.022533	-2.201	0.02908	*

A4. Summary Statistics

Year-round				
	Mu	Alpha	Theta	Beta
Multiple R^2:	0.2856	0.5664	0.5003	0.46
Adjusted R^2:	0.2475	0.546	0.4576	0.4029
p-value:	3.30E-09	2.2E-16	2.20E-16	1.96E-14

Rising				
	Mu	Alpha	Theta	Beta
Multiple R^2:	0.2981	0.5213	0.4663	0.3869
Adjusted R^2:	0.2563	0.4897	0.4243	0.3426
p-value:	2.53E-09	2.20E-16	2.20E-16	8.62E-13

Falling				
	Mu	Alpha	Theta	Beta
Multiple R^2:	0.2656	0.3578	0.2655	0.387
Adjusted R^2:	0.2355	0.3196	0.2264	0.3467
p-value:	2.91E-09	2.90E-12	2.68E-08	2.66E-13

A5. Correlation Matrix

	DA	Elev	Slope	Aspect	BFI	Clay	Sand	Silt	Biomass	Stem	Urban	Agro	Swamp	Grass	Peat	Rock	Decid	Oakpine	Boreal	Water	AugMeanAir	AugMaxAir	AugPrcp	FebMeanAir	FebMaxAir	FebPrcp
DA	1.00	-0.32	-0.06	0.19	0.10	-0.07	0.15	-0.15	-0.52	-0.32	0.36	-0.20	0.23	0.24	-0.01	0.03	-0.22	0.13	-0.04	0.51	0.27	0.27	0.00	0.26	0.28	-0.16
Elev	-0.32	1.00	0.50	-0.02	-0.62	0.47	-0.75	0.76	0.37	0.87	-0.60	-0.09	-0.41	-0.14	0.22	0.33	0.62	-0.53	0.39	-0.11	-0.88	-0.96	0.61	-0.84	-0.93	0.39
Slope	-0.06	0.50	1.00	-0.08	-0.68	0.49	-0.63	0.63	0.11	0.50	-0.42	-0.03	-0.64	0.00	-0.07	0.44	0.47	-0.33	0.01	-0.13	-0.50	-0.42	0.43	-0.53	-0.52	-0.03
Aspect	0.19	-0.02	-0.08	1.00	0.07	-0.08	-0.01	0.02	0.00	0.06	0.04	-0.26	0.12	-0.01	-0.11	0.07	0.15	-0.14	-0.11	0.28	0.01	-0.01	-0.16	0.00	-0.03	-0.05
BFI	0.10	-0.62	-0.68	0.07	1.00	-0.48	0.79	-0.80	-0.27	-0.62	0.32	0.01	0.54	-0.10	0.05	-0.28	-0.64	0.59	-0.10	0.19	0.64	0.55	-0.38	0.68	0.67	-0.18
Clay	-0.07	0.47	0.49	-0.08	-0.48	1.00	-0.75	0.69	0.13	0.26	-0.24	0.13	-0.44	-0.06	0.06	0.01	0.18	-0.13	0.13	0.02	-0.31	-0.37	0.48	-0.27	-0.34	-0.17
Sand	0.15	-0.75	-0.63	-0.01	0.79	-0.75	1.00	-1.00	-0.33	-0.68	0.41	0.04	0.47	0.04	-0.13	-0.28	-0.63	0.57	-0.22	0.05	0.73	0.72	-0.40	0.72	0.76	-0.26
Silt	-0.15	0.76	0.63	0.02	-0.80	0.69	-1.00	1.00	0.34	0.71	-0.42	-0.06	-0.46	-0.03	0.13	0.30	0.66	-0.60	0.23	-0.06	-0.75	-0.74	0.38	-0.75	-0.79	0.30
Biomass	-0.52	0.37	0.11	0.00	-0.27	0.13	-0.33	0.34	1.00	0.37	-0.28	0.01	-0.23	-0.12	-0.05	0.01	0.35	-0.26	-0.02	-0.31	-0.30	-0.34	0.02	-0.30	-0.35	0.13
Stem	-0.32	0.87	0.50	0.06	-0.62	0.26	-0.68	0.71	0.37	1.00	-0.67	-0.29	-0.27	-0.11	0.17	0.36	0.73	-0.61	0.33	-0.09	-0.92	-0.88	0.33	-0.91	-0.92	0.53
Urban	0.36	-0.60	-0.42	0.04	0.32	-0.24	0.41	-0.42	-0.28	-0.67	1.00	-0.11	0.31	0.27	-0.07	-0.13	-0.49	0.27	-0.12	0.11	0.58	0.60	-0.20	0.58	0.61	-0.18
Agro	-0.20	-0.09	-0.03	-0.26	0.01	0.13	0.04	-0.06	0.01	-0.29	-0.11	1.00	-0.28	-0.14	-0.12	-0.21	-0.09	0.03	-0.17	-0.24	0.13	0.15	0.04	0.12	0.13	-0.29
Swamp	0.23	-0.41	-0.64	0.12	0.54	-0.44	0.47	-0.46	-0.23	-0.27	0.31	-0.28	1.00	0.04	0.22	-0.09	-0.32	0.16	0.18	0.19	0.28	0.29	-0.42	0.29	0.35	0.24
Grass	0.24	-0.14	0.00	-0.01	-0.10	-0.06	0.04	-0.03	-0.12	-0.11	0.27	-0.14	0.04	1.00	-0.02	0.04	-0.07	0.01	-0.02	0.12	0.12	0.15	-0.04	0.11	0.12	-0.04
Peat	-0.01	0.22	-0.07	-0.11	0.05	0.06	-0.13	0.13	-0.05	0.17	-0.07	-0.12	0.22	-0.02	1.00	0.02	0.00	-0.09	0.76	0.08	-0.21	-0.21	0.20	-0.16	-0.14	0.53
Rock	0.03	0.33	0.44	0.07	-0.28	0.01	-0.28	0.30	0.01	0.36	-0.13	-0.21	-0.09	0.04	0.02	1.00	0.29	-0.29	0.07	-0.03	-0.42	-0.38	0.19	-0.42	-0.41	0.37
Decid	-0.22	0.62	0.47	0.15	-0.64	0.18	-0.63	0.66	0.35	0.73	-0.49	-0.09	-0.32	-0.07	0.00	0.29	1.00	-0.94	0.03	-0.11	-0.74	-0.64	0.03	-0.81	-0.79	0.37
Oakpine	0.13	-0.53	-0.33	-0.14	0.59	-0.13	0.57	-0.60	-0.26	-0.61	0.27	0.03	0.16	0.01	-0.09	-0.29	-0.94	1.00	-0.15	0.06	0.70	0.57	-0.01	0.77	0.71	-0.44
Boreal	-0.04	0.39	0.01	-0.11	-0.10	0.13	-0.22	0.23	-0.02	0.33	-0.12	-0.17	0.18	-0.02	0.76	0.07	0.03	-0.15	1.00	0.05	-0.41	-0.40	0.43	-0.34	-0.31	0.58
Water	0.51	-0.11	-0.13	0.28	0.19	0.02	0.05	-0.06	-0.31	-0.09	0.11	-0.24	0.19	0.12	0.08	-0.03	-0.11	0.06	0.05	1.00	0.06	0.03	-0.03	0.08	0.07	-0.05
AugMeanAir	0.27	-0.88	-0.50	0.01	0.64	-0.31	0.73	-0.75	-0.30	-0.92	0.58	0.13	0.28	0.12	-0.21	-0.42	-0.74	0.70	-0.41	0.06	1.00	0.94	-0.42	0.98	0.97	-0.58
AugMaxAir	0.27	-0.96	-0.42	-0.01	0.55	-0.37	0.72	-0.74	-0.34	-0.88	0.60	0.15	0.29	0.15	-0.21	-0.38	-0.64	0.57	-0.40	0.03	0.94	1.00	-0.51	0.89	0.96	-0.49
AugPrcp	0.00	0.61	0.43	-0.16	-0.38	0.48	-0.40	0.38	0.02	0.33	-0.20	0.04	-0.42	-0.04	0.20	0.19	0.03	-0.01	0.43	-0.03	-0.42	-0.51	1.00	-0.34	-0.41	0.05
FebMeanAir	0.26	-0.84	-0.53	0.00	0.68	-0.27	0.72	-0.75	-0.30	-0.91	0.58	0.12	0.29	0.11	-0.16	-0.42	-0.81	0.77	-0.34	0.08	0.98	0.89	-0.34	1.00	0.97	-0.56
FebMaxAir	0.28	-0.93	-0.52	-0.03	0.67	-0.34	0.76	-0.79	-0.35	-0.92	0.61	0.13	0.35	0.12	-0.14	-0.41	-0.79	0.71	-0.31	0.07	0.97	0.96	-0.41	0.97	1.00	-0.49
FebPrcp	-0.16	0.39	-0.03	-0.05	-0.18	-0.17	-0.26	0.30	0.13	0.53	-0.18	-0.29	0.24	-0.04	0.53	0.37	0.37	-0.44	0.58	-0.05	-0.58	-0.49	0.05	-0.56	-0.49	1.00

Appendix B – Principal Component Analysis

B1. PCA Loadings

Rank	PCA 1 (44.3%)		PCA 2 (10.8%)		PCA 3 (8.3%)		PCA 4 (7.0 %)	
1	FebMaxAir	0.303	Swamp	-0.443	DA	0.491	AugPrcp	0.507
2	FebMeanAir	0.297	Agro	0.389	Water	0.381	Peat	0.454
3	AugMeanAir	0.297	FebPrcp	-0.378	Biomass	-0.317	Decid	-0.368
4	Elev	-0.288	Water	-0.310	Slope	0.276	Aspect	-0.360
5	Stem	-0.287	Peat	-0.284	Grass	0.274	Oakpine	0.355
6	AugMaxAir	0.286	Aspect	-0.247	FebPrcp	-0.256	Biomass	-0.214
7	Silt	-0.270	Slope	0.246	BFI	-0.216	Elev	0.179
8	Sand	0.263	DA	-0.205	AugPrcp	0.207	AugMaxAir	-0.148
9	Decid	-0.252	BFI	-0.165	Sand	-0.202	FebPrcp	0.144
10	BFI	0.238	Silt	0.157	Silt	0.185	Elev	0.098
11	Oakpine	0.218	Oakpine	0.148	Aspect	0.184	Grass	-0.065
12	Slope	-0.199	Biomass	0.140	Swamp	-0.164	AugMeanAir	-0.057
13	Urban	0.196	Stem	-0.118	Urban	0.146	Urban	-0.056
14	Swamp	0.145	AugMeanAir	0.115	Agro	-0.144	Agro	0.039
15	FebPrcp	-0.144	FebMeanAir	0.105	Peat	-0.138	DA	0.038
16	AugPrcp	-0.138	AugMaxAir	0.101	Stem	-0.058	Water	0.036
17	Biomass	-0.135	Urban	-0.081	FebMeanAir	0.037	FebMeanAir	0.030
18	DA	0.107	FebMaxAir	0.076	AugMeanAir	0.035	Silt	-0.021
19	Water	0.050	Decid	-0.071	Decid	-0.032	Slope	0.012
20	Peat	-0.050	Sand	-0.067	Oakpine	0.031	Swamp	0.010
21	Grass	0.034	Grass	-0.056	AugMaxAir	0.027	Stem	0.007
22	Agro	0.025	Silt	0.046	FebMaxAir	0.015	FebMaxAir	-0.005
23	Aspect	0.007	Elev	0.000	Elev	-0.008	Sand	0.001

Rank	PCA 5 (5.5%)		PCA 6 (4.2%)		PCA 7 (3.4%)		PCA 8 (3.1%)	
1	Grass	0.492	Agro	-0.584	Grass	-0.411	Grass	-0.525
2	Aspect	-0.421	Grass	0.422	Biomass	0.381	Agro	-0.509
3	Urban	0.391	Biomass	0.410	Urban	0.381	Water	-0.374
4	Water	-0.286	Oakpine	0.313	Sand	-0.345	Slope	0.328
5	FebPrcp	0.270	DA	-0.249	Silt	0.323	Biomass	-0.230
6	BFI	-0.261	Decid	-0.187	Peat	0.320	Aspect	-0.180
7	Oakpine	-0.242	Stem	0.146	Aspect	0.299	DA	0.172
8	Peat	0.222	Aspect	0.141	Stem	-0.180	BFI	-0.129
9	AugMaxAir	0.152	Water	-0.135	FebMeanAir	0.159	Peat	-0.124
10	AugPrcp	-0.129	AugMeanAir	0.106	FebPrcp	0.121	Sand	0.123
11	Stem	-0.118	Peat	-0.105	Slope	-0.117	AugMaxAir	0.122
12	Silt	0.104	FebMeanAir	0.100	FebMaxAir	0.107	Elev	-0.117
13	Sand	-0.092	Elev	0.095	AugPrcp	0.095	Stem	0.084
14	AugPrcp	-0.085	AugMeanAir	0.069	Decid	-0.080	AugPrcp	-0.081
15	Decid	0.084	Urban	0.064	BFI	-0.076	Urban	0.066
16	FebMaxAir	0.065	Slope	0.052	AugMaxAir	0.061	Oakpine	0.060
17	Agro	0.048	AugMaxAir	-0.043	Swamp	-0.041	FebMaxAir	0.052
18	DA	0.034	Swamp	-0.041	Oakpine	-0.037	Decid	0.031
19	Swamp	0.030	FebMaxAir	0.024	Agro	0.016	AugMeanAir	0.027
20	AugMeanAir	0.028	Sand	0.019	FebPrcp	0.011	Swamp	0.025
21	Biomass	-0.027	Silt	-0.017	DA	0.008	Sand	0.018
22	FebMeanAir	-0.012	FebPrcp	-0.016	Water	0.008	Silt	-0.011
23	Slope	0.004	BFI	-0.009	Elev	0.002	FebMeanAir	-0.003

Rank	PCA 9 (2.7%)		PCA 10 (2.5%)		PCA 11 (2.0%)		PCA 12 (1.6%)	
1	Urban	-0.500	Aspect	-0.582	Water	0.529	DA	0.553
2	Peat	0.486	Water	0.350	Swamp	-0.416	Biomass	0.508
3	AugPrcp	-0.411	Biomass	0.345	DA	-0.353	Sand	0.301
4	Slope	0.350	Peat	-0.295	Urban	0.269	Silt	-0.291
5	AugMaxAir	0.199	AugPrcp	-0.255	Aspect	-0.264	AugPrcp	0.260
6	Elev	-0.172	DA	0.214	Agro	-0.231	Decid	0.217
7	Water	0.146	Sand	-0.203	Oakpine	-0.210	Oakpine	-0.200
8	Oakpine	0.145	Silt	0.195	Decid	0.193	Peat	0.195
9	FebMaxAir	0.143	Swamp	0.194	Sand	0.182	Urban	-0.146
10	Slope	-0.132		-0.183	Silt	-0.178	FebPrcp	-0.144
11	AugMeanAir	0.130	Oakpine	0.157	Grass	-0.137	Water	-0.096
12	Silt	0.125	Decid	-0.125	BFI	0.135	Slope	0.079
13	Swamp	-0.114	Grass	-0.103	Slope	0.135	Aspect	-0.078
14	Grass	0.100	AugMaxAir	-0.097	AugMaxAir	0.086	AugMaxAir	0.042
15	FebMeanAir	0.088	Agro	-0.054	Peat	0.081	Elev	0.033
16	Biomass	0.064	Urban	-0.049	AugPrcp	0.071	AugMeanAir	0.031
17	Stem	0.056	FebPrcp	-0.049	Stem	-0.053	Agro	-0.025
18	Decid	0.035	BFI	-0.033	Biomass	0.040	FebMaxAir	0.020
19	FebPrcp	0.027	FebMaxAir	-0.031	FebMeanAir	-0.036	Stem	-0.014
20	DA	-0.026	Stem	0.028	Elev	-0.035	BFI	0.010
21	Agro	-0.016	AugMeanAir	-0.026	AugMeanAir	0.023	FebMeanAir	0.005
22	BFI	0.016	Elev	-0.020	FebPrcp	0.018	Grass	-0.004
23	Aspect	0.007	FebMeanAir	-0.007	FebMaxAir	0.001	Swamp	0.000

Rank	PCA 13 (1.3%)		PCA 14 (1.0 %)		PCA 15 (0.9%)		PCA 16 (0.7%)	
1	FebPrcp	-0.666	Swamp	-0.539	BFI	-0.706	AugPrcp	-0.387
2	Swamp	0.452	Slope	-0.507	Slope	-0.422	FebPrcp	-0.356
3	DA	-0.234	AugPrcp	-0.236	Urban	-0.279	BFI	-0.352
4	Oakpine	-0.210	DA	0.220	AugPrcp	0.177	Urban	0.338
5	Peat	0.202	Water	-0.218	AugMeanAir	0.168	Peat	0.277
6	Agro	-0.188	BFI	0.206	DA	-0.165	Decid	-0.264
7	Aspect	-0.171	Agro	-0.201	AugMaxAir	0.164	FebMeanAir	-0.241
8	Decid	0.168	Elev	0.192	Water	0.145	Sand	0.235
9	BFI	0.165	Biomass	-0.185	FebMeanAir	0.133	AugMeanAir	-0.219
10	Sand	-0.137	AugMaxAir	-0.165	FebMaxAir	0.131	Stem	0.217
11	Biomass	-0.134	FebPrcp	-0.158	Agro	-0.121	Silt	-0.206
12	Elev	0.129	Decid	0.147	Decid	0.116	Oakpine	0.178
13	Silt	0.093	Peat	0.138	Biomass	-0.105	FebMaxAir	-0.162
14	Water	-0.086	FebMeanAir	0.121	Stem	0.088	Agro	0.097
15	Stem	-0.077	AugMeanAir	0.100	Silt	-0.084	Grass	-0.066
16	Slope	0.069	Aspect	-0.083	Grass	-0.082	AugMaxAir	-0.063
17	AugMeanAir	0.068	Sand	-0.075	Sand	0.078	Elev	0.058
18	AugPrcp	0.052	Silt	0.073	Swamp	0.066	Aspect	0.058
19	FebMeanAir	0.045	FebMaxAir	-0.070	Peat	0.047	Slope	0.041
20	FebMaxAir	-0.041	Stem	0.057	FebPrcp	-0.038	Swamp	-0.041
21	AugMaxAir	-0.039	Urban	-0.037	Oakpine	-0.025	Biomass	0.029
22	Grass	0.026	Grass	0.034	Elev	0.025	DA	0.029
23	Urban	0.002	Oakpine	0.022	Aspect	-0.016	Water	0.015

Rank	PCA 17 (0.3%)		PCA 18 (0.2%)		PCA 19 (0.1%)		PCA 20 (0.04%)	
1	Elev	-0.577	Stem	0.824	FebMaxAir	0.568	Elev	0.597
2	FebMeanAir	-0.420	AugMaxAir	0.306	AugMaxAir	-0.496	FebMaxAir	0.416
3	AugMeanAir	-0.373	Agro	0.190	AugMeanAir	-0.436	AugMaxAir	0.414
4	Slope	-0.270	BFI	0.183	FebMeanAir	0.406	AugMeanAir	-0.352
5	AugMaxAir	0.268	AugMeanAir	0.178	Elev	-0.167	Stem	-0.208
6	AugPrcp	0.237	Urban	0.178	Oakpine	-0.130	Decid	-0.202
7	FebPrcp	-0.192	FebMaxAir	0.158	Stem	0.123	FebMeanAir	-0.168
8	BFI	0.136	FebMeanAir	0.149	Slope	0.061	Oakpine	-0.151
9	Sand	-0.124	Elev	0.135	BFI	-0.059	AugPrcp	-0.111
10	Stem	0.123	Oakpine	-0.091	Silt	-0.046	Urban	-0.092
11	FebMaxAir	0.115	AugPrcp	0.076	FebPrcp	-0.045	Agro	-0.081
12	Swamp	-0.107	Sand	-0.069	AugPrcp	-0.036	Peat	-0.065
13	Agro	-0.105	Swamp	0.050	Decid	0.029	Sand	-0.048
14	Silt	0.104	Peat	-0.045	DA	-0.028	BFI	0.045
15	Urban	-0.086	DA	0.043	Swamp	-0.024	Swamp	-0.035
16	Water	-0.065	Aspect	-0.040	Urban	0.024	DA	0.027
17	Decid	-0.048	Silt	0.034	Sand	0.015	Silt	-0.026
18	Peat	0.044	Water	0.031	Biomass	-0.012	Slope	-0.024
19	Biomass	0.025	Biomass	-0.021	Aspect	-0.010	FebPrcp	0.015
20	Oakpine	0.023	Slope	0.010	Agro	0.010	Grass	0.007
21	Grass	0.021	FebPrcp	-0.007	Peat	0.007	Aspect	0.005
22	DA	-0.015	Grass	-0.004	Grass	0.000	Biomass	-0.001
23	Aspect	0.006	Decid	-0.001	Water	0.000	Water	0.001

Rank	PCA 21 (0.01%)		PCA 22 (0.01%)		PCA 23 (0.01%)	
1	Decid	-0.681	FebMeanAir	0.5598	Silt	-0.673
2	Oakpine	-0.620	FebMaxAir	-0.494	Sand	-0.635
3	AugMeanAir	0.216	AugMeanAir	-0.4406	FebMeanAir	-0.237
4	Urban	-0.186	AugMaxAir	0.31632	AugMeanAir	0.195
5	AugMaxAir	-0.132	Silt	-0.2714	AugMaxAir	-0.151
6	Elev	-0.126	Sand	-0.2525	FebMaxAir	0.148
7	FebMaxAir	-0.108	Elev	-0.0559	Decid	0.034
8	Swamp	-0.104	Decid	-0.0551	Oakpine	0.029
9	Agro	-0.100	Oakpine	-0.0468	FebPrcp	0.025
10	Stem	0.04963	Urban	-0.036	Urban	0.02353
11	Water	-0.0224	Agro	-0.021	AugPrcp	-0.018
12	FebPrcp	-0.0205	Stem	-0.021	BFI	-0.0157
13	AugPrcp	-0.0185	Slope	-0.014	Aspect	0.0099
14	Peat	-0.0177	Swamp	-0.009	Agro	0.00912
15	BFI	-0.0164	FebPrcp	0.009	Slope	0.00855
16	Grass	-0.0098	Biomass	0.008	Elev	-0.0073
17	Slope	0.00791	Aspect	-0.007	Stem	0.0059
18	Sand	0.00607	Grass	0.003	Water	-0.0051
19	Silt	-0.0048	Peat	0.002	DA	0.00471
20	DA	-0.0043	BFI	-0.001	Biomass	0.00402
21	Aspect	-0.0033	DA	0.001	Grass	0.00291
22	Biomass	0.00326	Water	0.000	Swamp	-0.0017
23	FebMeanAir	0.00317	AugPrcp	0.000	Peat	-0.0012

B2. PCA Significance to Each Nonlinear Model Parameter

PCA Significance to Each Parameter				
	Mu	Alpha	Theta	Beta
Intercept	3	1	1	1
1		1		1
2		1	1	3
3	4	1		1
4				
5		2		1
6			4	
7	2			3
8				
9		2	1	4
10			4	
11	4		2	
12	4	1		
13		4	3	
14				4
15		4	2	
16				
17			3	
18				
19				2
20			2	
21				
22		4	4	3
23				

Appendix C - Calibration

C1. Comparison of parameters under standard and hysteresis methods of calibration.